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Dmitry Ivanov

Structural Dynamics and Resilience in Supply Chain Risk Management



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Structural Dynamics and Resilience in Supply Chain Risk Management



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I dedicate this book to my lovely family

“It is not about improving accuracy of the forecast and reducing the amount of uncertainty in the future, it is about eliminating the need for certainty.”

Ronald W. Bohl

Preface

Purpose and Content of the Book

This book offers an introduction to structural dynamics and disruption risk management in the supply chains for larger audiences. It covers recent developments in supply chain risk management and resilience from the position of structural dynamics focusing on the disruption propagation and the ripple effect.

Structural dynamics in a supply chain results both from planned redesign actions and from disruptive events such as natural catastrophes, strikes, piracy, and man-made disasters. This book explores supply chain structural dynamics and control, with an emphasis on global network design with disruption consideration, distribution planning, and dynamic (re)scheduling. Based upon the triangle, “management problem—mathematical model—technology,” the book derives practical recommendations for management decision-making with disruption risk consideration for the following areas:

- What is the impact of the disruption on operational and financial supply chain performance?
- What parts of the supply chain are affected by the disruption, i.e., what is the scope of disruption propagation?
- Is stabilization or recovery needed? If yes, what changes and at which stages in the supply chain are needed?
- When does one failure trigger an adjacent set of failures?
- Which supply chain structures are particularly sensitive to ripple/domino effect?
- What are the typical ripple effect scenarios and how to react in each of these scenarios in the most efficient manner?
- How to estimate the impact of possible disruptions on performance in the proactive stage
- How to estimate the impact of real disruptions on performance in the execution stage
- How to generate efficient and effective stabilization and recovery measures

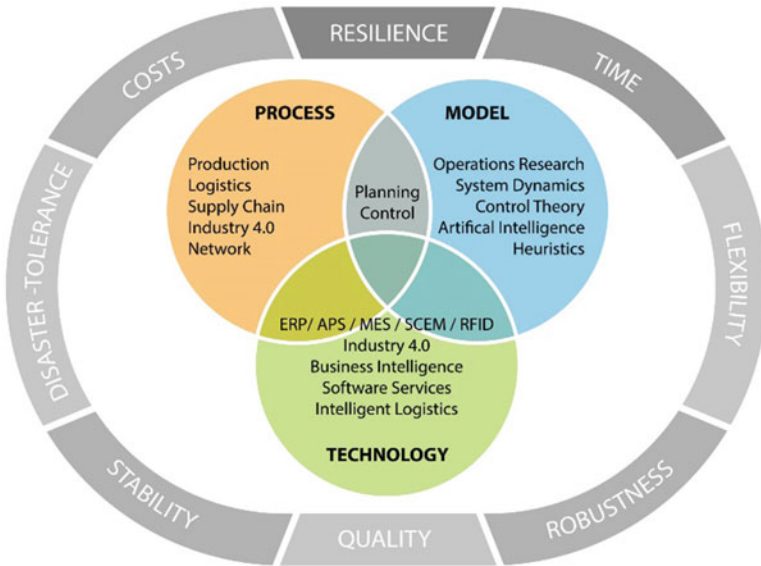


Fig. 1 Research philosophy behind this book

Among others, this book considers the ripple effect in the supply chain (also known as the “domino effect,” “cascading effect,” and “snowball effect”). It examines examples from both industrial and service supply chains and reveals decision-making recommendations for tackling disruption risks in proactive and reactive domains.

Based upon the triangle, “process–model–technology,” this book investigates the dynamics of complex networks in production, logistics, and supply chains (Fig. 1).

In the management section, without relying heavily on mathematical derivations, the book offers state-of-the-art concepts and methods to tackle supply chain disruption risks in a simple, predictable format to make it easy to understand for students and professionals with both management and engineering background. This part of the book conceptualizes supply chain structural dynamics domain and disruption risks in verbal format.

In the technical section, the book constitutes structural dynamics control methods for supply chain management. Subsequently, real-life problems are modelled and solved with the help of mathematical programming, discrete-event simulation, optimal control theory, and fuzzy logic (Fig. 2).

The ultimate objective of this book is to comprehensively present an original multidisciplinary view of supply chain structural dynamics control developed by the author during the last 15 years. Providing supply chain risk managers and analysts with working models for contemporary decision-making problems at supply chain design, planning, and control levels, this research also aims at

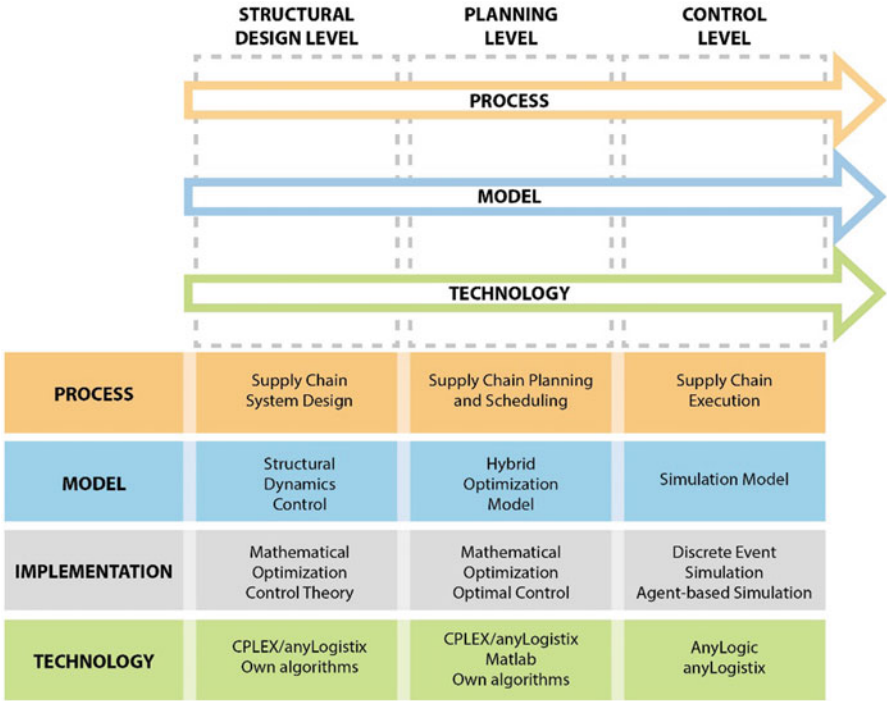


Fig. 2 Book structure

contributing to fundamentals of structural dynamics control in complex systems in general.

Chapter 1 first delineates the fundamentals of structural dynamics control in complex systems. Subsequently, the reader is introduced to the supply chains and their structural dynamics. Finally, the technical description of supply chain structural dynamics control is elaborated.

Chapter 2 introduces the reader to supply chain risk management as the application area of the structural dynamics control theory. Major definitions with regard to uncertainty and risks are followed by differentiating operative and disruptive risks. Subsequently, bullwhip and ripple effects are described. The latter is analyzed in more detail since the ripple effect is closely related to supply chain structural dynamics.

Chapter 3 defines the resilience concept in the framework of supply chain management. Major definitions with regard to resilience, robustness, stability, and flexibility are followed by a control theoretic supply chain resilience framework. Subsequently, a fuzzy theoretic approach to supply chain robustness estimation in the presence of structural dynamics is presented. The chapter concludes by presenting verbal and formal algorithms for supply chain structural and parametric adaptation.

Having described the structural dynamics control theory and the supply chain risk management domain as the application area, Chaps. 4 and 5 delineate methodical aspects. In Chap. 4, basic principles and methods of model-based decision-making such as mathematical optimization, simulation, control theory, and heuristic algorithms are described. Building upon Chap. 4, the state of the art in application of model-based decision-making methods to supply chain structural dynamics analysis and control is analyzed. Recent contributions from mathematical optimization, simulation, and control theory are summarized and analyzed in regard to the created knowledge and still existing research gaps.

Chapters 6, 7, 8, and 9 present applications of mathematical optimization, simulation, and control theory to solutions of supply chain design, planning, and scheduling models with structural dynamics consideration.

Chapter 6 considers a multistage supply chain reconfiguration problem. It develops a hybrid multi-objective mathematical optimization–optimal control model for proactive supply chain recovery planning and illustrates its application on numerical examples. The particular feature of the technical approach is the separation of design and control variables into a static (i.e., linear programming) and dynamic (i.e., optimal control) models. The management problem statement is original with regard to simultaneous decisions on supply chain redesign and replanning in the case of severe disruptions.

Chapter 7 is devoted to multistage supply chain scheduling. It develops control theoretic models and algorithms for supply chain scheduling with capacity disruption and recovery considerations. In this chapter, an original approach to flow shop and job shop scheduling with the help of optimal control theory blended with mathematical optimization is presented. Supply chain scheduling models are based on a dynamic interpretation of job execution processes. The computational procedure implies transformation of the optimal control problem to a boundary problem and Hamiltonian maximization with the help of maximum principle. The formulation of the scheduling problem in terms of optimal control allows for the utilization of a variety of control theoretic tools such as attainable sets and feedbacks to scheduling theory and practice. In addition, continuous time and state variables allow for modelling detailed operation execution dynamics with nonstationary considerations as well as modelling continuous flow production systems.

Chapter 8 elaborates on the simulation applications to supply chain structural dynamics control. The chapter presents three models with different application areas in industrial, retail, and service supply chains. The objective of this chapter is to reveal and depict advantages of simulation modelling as a dynamic approach to supply chain disruption management. The models developed provide evidence that simulation techniques are powerful tools that allow extending optimization methods. On the technical side, models are developed as discrete-event simulation models with multi-agent elements in AnyLogic and anyLogistix.

Chapter 9 considers a system theoretic concept of entropy with regard to supply chain complexity and adaptability analysis. A new concept of supply chain adaptation potential is presented and illustrated in the numerical examples. The

application of this new method to the selection of the supply chain design method is also depicted.

Chapter 10 concludes the book. It starts with four case studies which illustrate practical handling of supply chain structural dynamics in risk management of the companies. Subsequently, it elaborates on new drivers of supply chain structural dynamics. The focus is directed herewith in the Industry 4.0 and cyber-physical systems. The adaptive supply chain management concept concludes this chapter.

Target Audience

Management and engineering graduate and PhD students, supply chain and operations management professionals, supply chain risk managers and analysts, industrial engineers, control engineers, and operations and supply chain researchers.

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The author gratefully acknowledges all those who have helped bring this book to publication. First and foremost, I have greatly benefited from the wealth of a vast array of published materials on the subject of supply chain risk management and associated topics. I would like to thank the coauthors of research papers that had been published in recent years. The content of this book has benefited immensely from their valued insights, comments, and suggestions. My sincere thanks to Prof. Dr. Eng. Boris Sokolov, Prof. Dr. Eng. Alexandre Dolgui, and Dr. Eng. Alexander Pavlov who contributed immensely to the research described in selected chapters of this book. I would also like to acknowledge gratefully the contribution of Dr. Semen Potryasaev, Dr. Dmitry Pavlov, Mr. Maxim Rozhkov, Prof. Dr. Alexander Arkhipov, and Dr. Marina Ivanova. With regard to the manuscript preparation, I thank Ms. Meghan Stewart and Mr. John Davis at Berlin School of Economics and Law for thorough proofreading of the manuscript as well as students Ms. Tamara Erdenberger, Ms. Lisa Sagur, and Mr. Adish Tamboli for their technical assistance. Finally, I wish to thank Dr. Camille Price, Series Editor, and the entire Springer production team for their assistance and guidance in successfully completing this book. Last but not least, I cordially thank my family for enormous support during the work on this book.

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His *research* explores supply chain structural dynamics and control, with an emphasis on global supply chain design with disruption consideration, distribution planning, and dynamic rescheduling. He is coauthor of structural dynamics control methods for supply chain management. He applies mathematical programming, simulation, control, and fuzzy theoretic methods. Based upon triangle “process–model–technology,” he investigates the dynamics of complex networks in production, logistics, and supply chains. Most of his courses and research focuses on the interface of supply chain management, operations research, industrial engineering, and information technology.

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He has been guest editor of special issues in different journals, including the *International Journal of Production Research* and the *International Journal of Integrated Supply Management*. He is an associate editor of the *International Journal of Systems Science* and editorial board member of several international and national journals, e.g., the *International Journal of Systems Science: Operations and Logistics* and the *International Journal of Inventory Research*.

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Chapter 1

Supply Chain Management and Structural Dynamics Control

1.1 Structural Dynamics and Supply Chains

Structural dynamics is a theory that originated in the field of earthquake engineering and computational mechanics (Paz 1990; Clough and Penzien 1993; Chopra 2011; Humar 2012). The major principles of structural dynamics theory relate to discrete and continuous systems subject to mechanical system response to dynamic loads. Another industry stream of structural dynamics theory has been developed in the aerospace control in the area of complex structure coordination (Kalinin and Sokolov 1996; Okhtilev et al. 2006). Generally speaking, engineering approaches to structural dynamics control dealt with coordination of complex networks, the behaviour of which may be affected by internal and external disturbances.

In management, supply chains represent complex coordinated networks that operate in uncertain environments and are therefore exposed to different risks and disruptions (Chopra et al. 2007; Dolgui and Proth 2010; Simchi-Levi et al. 2015; Martel and Klibi 2016; Ivanov et al. 2017). In such systems, the issues of structural dynamics controls are of vital theoretical and practical importance. Supply chains resemble engineering control systems in areas such as feedback mechanisms, adjustment loops, and generation of performance over time (Disney et al. 2006; Sarimveis et al. 2008; and Ivanov et al. 2012).

Several assumptions must be accepted with regards to control theory. *First* is a strong contribution of control theory to supply chain management as an adaptive understanding of planning and control processes. *Second*, an advantage of control theory is the consideration of non-stationary and non-linear processes in the continuous time domain. Continuous dynamic models let us establish and optimize supply chain performance indicators in dynamics that are difficult to express within static and discrete time models. *Third*, the possibility of covering supply chain dynamics at the process level as well as changes in the supply chain environment are also strong contributor to control theory. *Fourth*, control theory allows for the

simultaneous structural functions synthesis of supply chain design and the integrated solution of supply chain planning problems in the system as a whole. *Finally*, by using control theory, important categories of supply chain analysis such as stability, robustness and adaptability can be taken into consideration.

However, some peculiarities of supply chains as technical-organizational systems that do not allow a direct application of control theoretic methods. For this purpose, a combined application of control theory, mathematical optimization, and simulation techniques can be favourable. In addition, *ipso facto* that supply chain planning and scheduling can be formulated as optimal control problems (Ivanov et al. 2012, 2016) is a great advantage subject to further dynamics analysis that is a crucial application area of control theory to supply chain management. In this area, control theory can be applied to supply chain management to a greater extent and enlarge the scope of supply chain dynamics analysis that is currently rather limited.

A *supply chain* is a network of organizations and processes wherein a number of various enterprises (suppliers, manufacturers, distributors and retailers) collaborate (cooperate and coordinate) along the entire value chain to acquire raw materials, to convert these raw materials into specified final products, and to deliver these final products to customers (Ivanov et al. 2017).

Supply chains are dynamic systems subject to both structural and parametrical changes. The main supply chain features is the multiple structure design and changeability of structural parameters because of objective and subjective factors at different stages of the supply chain life cycle. In other words, supply chain *structural dynamics* is constantly encountered in practice (Ivanov and Sokolov 2010; Ivanov et al. 2010; Hasani and Khosrojerdi 2016; Mistree et al. 2017).

Decisions in supply chain structural dynamics control can be roughly classified into proactive and reactive stages (Fig. 1.1).

Resilient supply chain design extends traditional supply chain design approaches with regard to the incorporation of redundancies such as back-up facilities, inventory and capacity flexibility. These redundancies create, at the proactive planning stage, some flexibility that can be used at the reactive control stage in the case of disruptions in supply chain structures in order to recover system performance and operational processes.

Figure 1.2 depicts major structures and their changes in dynamics. The composition of different structures at different point in time results in supply chain multi-structural macro-states S . Multi-structural macro-states describe supply chain design evolution over time due to planned (controllable) and uncertain factors.

The multi-dimensional dynamic space along with coordinated and distributed decision-making guides us to understanding modern supply chains as *multi-structural dynamic systems* (Ivanov et al. 2010).

The main supply chain structures are as follows:

- product structure (bill-of-materials),
- functional structure (structure of management functions and business-processes),
- organizational structure (structure of facilities, enterprises, managers and workers),

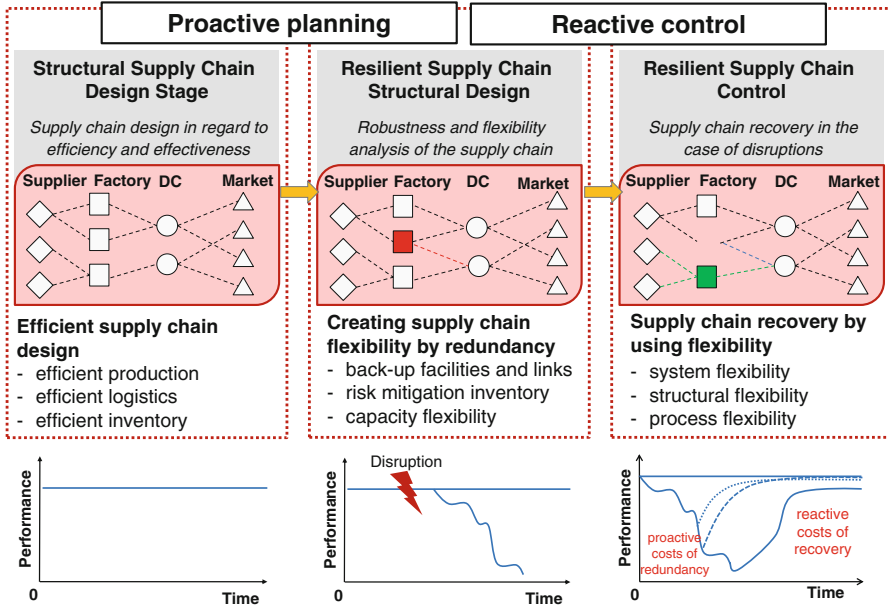


Fig. 1.1 Supply chain structural dynamics control

- technical-technological structure (structure of technological operations for manufacturing, structure of machines, devices etc.),
- topological structure (roads, modes of transportation, etc.) structure,
- informational structure (information flows according to a coordination strategy in the supply chain), and
- financial structure (structure of costs and profit centres).

Additional structures, e.g., energy structure, can be added within specific contents. The above-mentioned description of supply chains as dynamic systems with structural changes can be used as a framework for analysis of the existing research and identifying missing links in current research and needs for future research. It represents the main supply chain structures with regards to which research can be performed. It explicitly incorporates structural dynamics aspects which inevitably exist in all supply chain applications. In addition, structural dynamics explicitly relates different structures which are tightly interlinked with each other in practice.

Consider some examples of factors that may cause supply chain structural dynamics and management practices that companies apply to structural dynamics control. Recent examples of such severe disruptions include the earthquake and resulting tsunami in Japan on 11 March 2011, which rippled quickly through supply chains worldwide (Marsh et al. 2011; Park et al. 2013). As a result, Toyota lost its position as the major car manufacturer in terms of production volumes for that year. Many other industries worldwide were also hard hit by the shortage of chemicals components produced in Japan. Another example is the floods in Thailand which

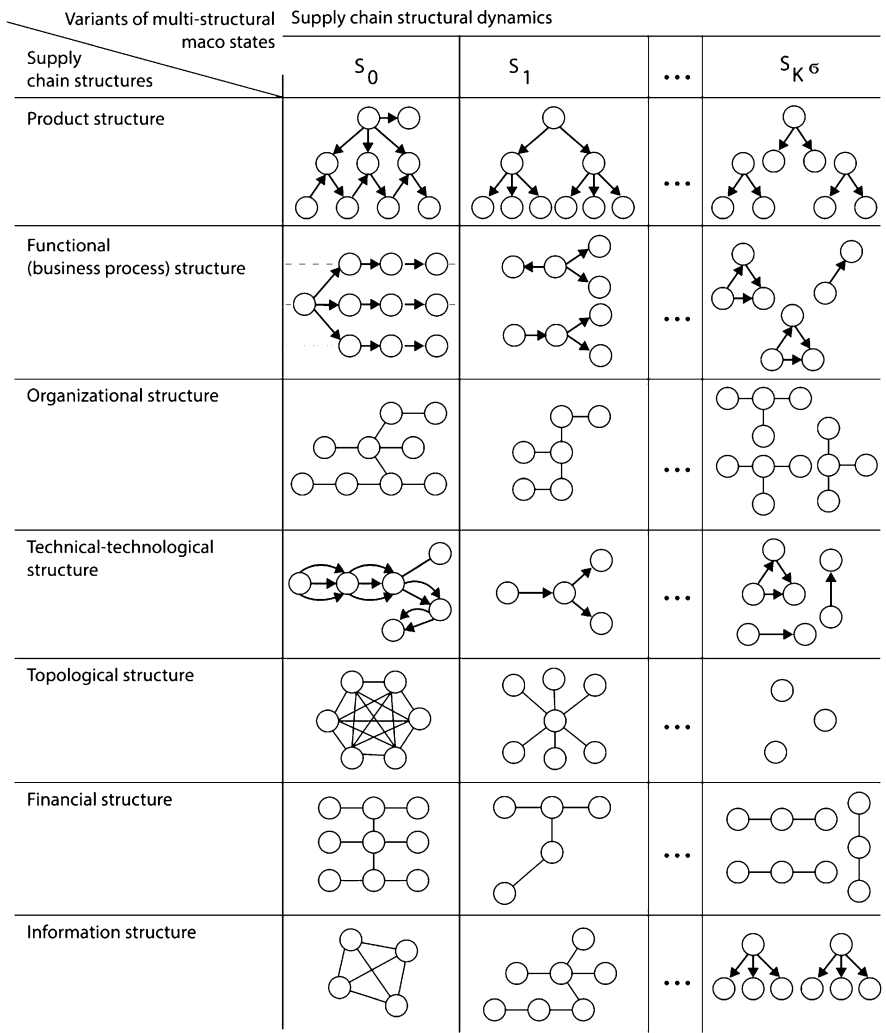


Fig. 1.2 Supply chain multi-structural composition and structural dynamics (Based on Ivanov et al. 2010)

had a serious impact on the high tech sector. Intel claimed to have lost \$1 billion in sales during the fourth quarter of 2011 as computer producers were not buying chips from Intel due to their being unable to source the hard drives needed to make new machines.

A fire in the Phillips Semiconductor plant in Albuquerque, New Mexico, caused its major customer, Ericsson, to lose \$400 million in potential revenue. Hurricane Katrina halted 10–15% of total US gasoline production, raising both domestic and overseas oil prices (Canadian Competition Bureau 2006). The global price of coffee

rose by 22% after Hurricane Mitch, which also affected supply chains worldwide, struck the Central American Republics of Nicaragua, Guatemala, and Honduras, (Fairtrade Foundation 2002). A survey by the Business Continuity Institute (2011) found that 85% of companies with global supply chains have experienced at least one supply chain disruption in the previous 12 months. The costs of such disruption include lower revenue, increased downtime, delays in delivery, lost customers, and damaged reputations.

With regards to supply chain structural dynamics control, for example, Toyota extended its supply chain by using a multiple-sourcing strategy and by building new facilities on the supply side. Amazon prefers holding fast-moving items in distribution centres while slow-moving items tend to be stored centrally. Apple localized production in China but the distribution network is global. Such supply chain segmentation also helps to reduce disruption risk implications (Chopra and Sodhi 2004). Samsung tends to have at least two suppliers even if the second one provides only 20% of the volume (Sodhi and Lee 2007). Online fashion retailer ASOS was badly affected by a fire in a UK warehouse in 2005 after which operations were stopped for 1 month. They developed a contingency policy for such disruptions. The policy included establishing an additional warehouse in Asia. This helped the company to recover within only 2 days in June 2014 when new fire occurred in another of their UK warehouses.

Hendricks and Singhal (2005) quantified the negative effects of supply chain disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started 1 year before and ended 2 years after a disruption.

Let us introduce some basic definitions of the supply chain structural dynamics control approach (see Fig. 1.3).

The *processes* and *flows* within the structures are implemented through resource replenishment and consumption. These *resources* may be related to materials, time, information, people and finances. In order to utilize these resources, a number of *operations* needs to be planned and executed. The execution happens not statically but dynamically, and is unwound over different time horizons. Through structural and operations dynamics, supply chains may appear in different *states*. The above-mentioned components are tightly interlinked.

Operations are activities to be performed subject to specified goals. A group of these activities is called a *process*. The fulfilment of jobs is subject to *resource availability*. We understand resources to be machine capacities, materials, and time. These resources are limited and their availability varies dynamically. During operation execution, different *flows* (material, information, and financial) are consumed with dynamically changing intensities.

Structure represents supply chain elements and their interrelations.

Supply chain macro-state is a general supply chain state in which one or more supply chain objects can operate and fulfil jobs and processes.

Structural state is a supply chain macro-state that reflects the current states of objects in a supply chain structure as well as interrelations between these objects.

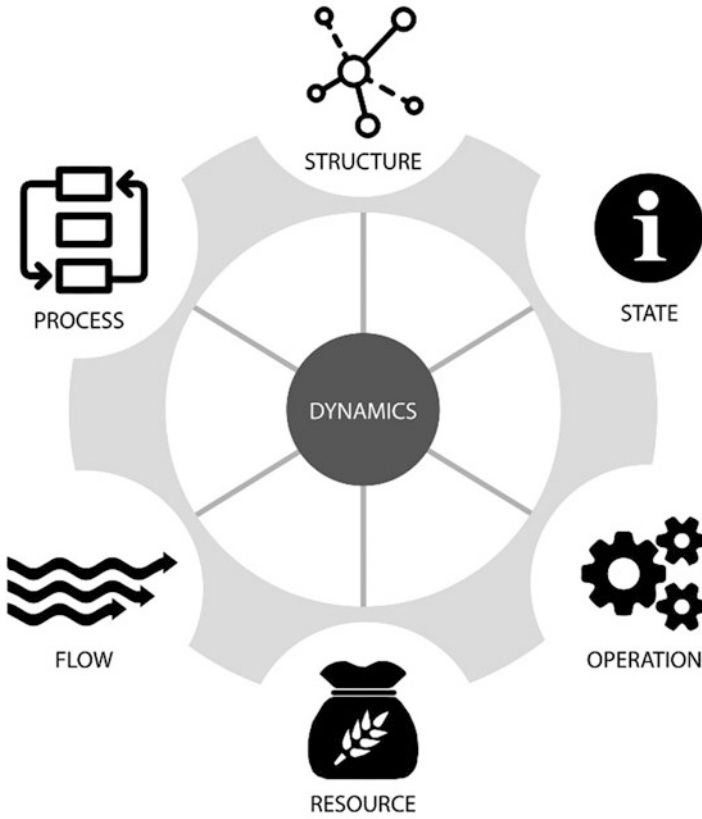


Fig. 1.3 Main components of supply chain structural dynamics

Multi-structural macro-state is a supply chain macro-state that reflects the current states of objects and structures in supply chains as well as the interrelations between them.

Collaboration zone is the part of the whole supply chain in a current multi-structural macro-state that reflects structural elements (decision-makers, processes, products, control variables, constraints, goals, perturbations, etc.) which are involved in decision-making on supply chain (re)planning within a certain period of time (so called interval of structural constancy).

Structural dynamics is the process of supply chain structural transition from one planned macro-state to another.

Structural dynamics control is the process of producing control inputs and implementing supply chain transition from the current macro-state to a planned one (in the planning mode) or any other feasible state (in the disruption-recovery mode) in which the supply chain adaptation can be performed and the desired performance can be achieved over the given period of time.

Let us present an example of supply chain structural dynamics control description (Ivanov et al. 2010).

- Class 1. Organizational structure: structure of enterprises, management departments, and workers.
 - Subclass 1.1. Structure of enterprises: competencies, location, etc.
 - Subclass 1.1.1. Competencies: capacities, costs, reliability, quality.
 - Subclass 1.1.2. Collaboration of enterprises.
- Class 2. Business process structure: coordination parameters (demand, inventories, or orders), jobs (distribution, production, replenishment; matched with subclasses), functions (in relations with the management departments)
- Class 3. Product structure: product variety, demand, bill of material, etc.
- Class 4. Technological structure: operations, machines (in relation to the technical devices of the subclass 1.1), quality data, etc.
- Class 5. Topological structure (locations, movements, etc.).
- Class 6. Financial structure (costs and profit centres).

In recent years, research on supply chains has been broadened to cover supply chain dynamics. In these settings, control theory is becoming of even greater interest to researchers and practitioners (Ivanov et al. 2012). This book joins this research stream. In this research, we apply control theory in combination with mathematical optimization to model supply chain structural dynamics. It considers supply chain design, planning and scheduling from the perspectives of adaptable, stable, and adjustable facility structures plans and schedules that enable the achievement of management goals in both “ideal” optimal solutions and in a real perturbed execution environment.

In the approach presented, supply chain optimization will be considered from the perspectives of the entire value chain and as a function of the achievement of management goals. The developed approach aims to provide advanced insights into supply chain dynamics and constructive ways to transition from simple open time slots and incremental planning to dynamic, feedback-based adaptive and integrated supply chain planning and scheduling to implement adaptability, stability, and crisis-resistance throughout the value chain.

1.2 Basics of Supply Chain Management

Supply chain management is a cross-department and cross-enterprise integration and coordination of material, information and financial flows to transform and use the supply chain resources in a most rational way along the entire value chain, from raw material suppliers to customers. Supply chain management is one of the key components of any organization and is responsible for balancing demand and supply along the entire value-adding chain (Ivanov et al. 2017).

Supply chain management integrates production and logistics processes (Chopra and Meindl 2015). In practice, production, logistics and supply chain management problems interact with each other and are tightly interlinked. Only two decades have passed since enterprise management and organizational structure have been considered from the functional perspective which includes marketing, research and development, procurement, warehousing, manufacturing, sales, and finance. The development of supply chain management was driven in the 1990s by three *main trends*: customer orientation, markets globalization and establishing an information society. These trends caused changes in enterprise competitive strategies and required new adequate value chain management concepts.

Supply chain management is one of the key components of enterprise management and is responsible for balancing demand and supply along the entire value-adding chain (Christopher 2011). Supply chain management's impact on enterprise management can be estimated as up to 30%. Decisions concerning supply chain configuration make up 80% of total supply chain costs (Harrison 2005) and up to 75% of the operational costs in supply chains (Wannenwetsch 2005).

The first use of the term "Supply Chain Management" is commonly related to the article "Supply Chain Management: Logistics Catches up with Strategy" by Oliver and Webber (1982). They set out to examine material flows from raw material suppliers through the supply chain to end consumers within an integrated framework that has been called supply chain management. The origins of supply chain management can be seen in early works on postponement, system dynamics and the bullwhip effect (Forrester 1961), cooperation (Bowersox 1969), multi-echelon inventory management (Geoffrion and Graves 1974), JIT (just-in-time), and lean production.

Supply chain management, as the term implies, is primarily directed at the inter-organizational level. Another successful application of supply chain management depends to a very large extent on intra-organizational changes. Even collaborative processes with extensive information systems applications are managed by people who work in different departments: marketing, procurement, sales, production, etc. The interests of these departments are usually in conflict with each other. Hence, not only outbound synchronizations but also internal organizational synchronization is encompassed by supply chain organization.

Let us consider supply chain management as a system within enterprise management (see Fig. 1.4).

Supply chain management is subject to the goals of the superordinated strategic management level and should be harmonized with the enterprise competitive strategy, given constraints (i.e., financial constraints) and risks (the achievement of potential supply chain goals is always subject to a certain amount of risk due to uncertainty).

Supply chain management within an enterprise is based on both enterprise-internal activities and interactions with external interrelated systems. These systems are customers and suppliers. Supply chain management is in turn the goal-set system for the underordinated systems, e.g., a production system.

The decision-making areas in supply chain management are shown in Fig. 1.5.

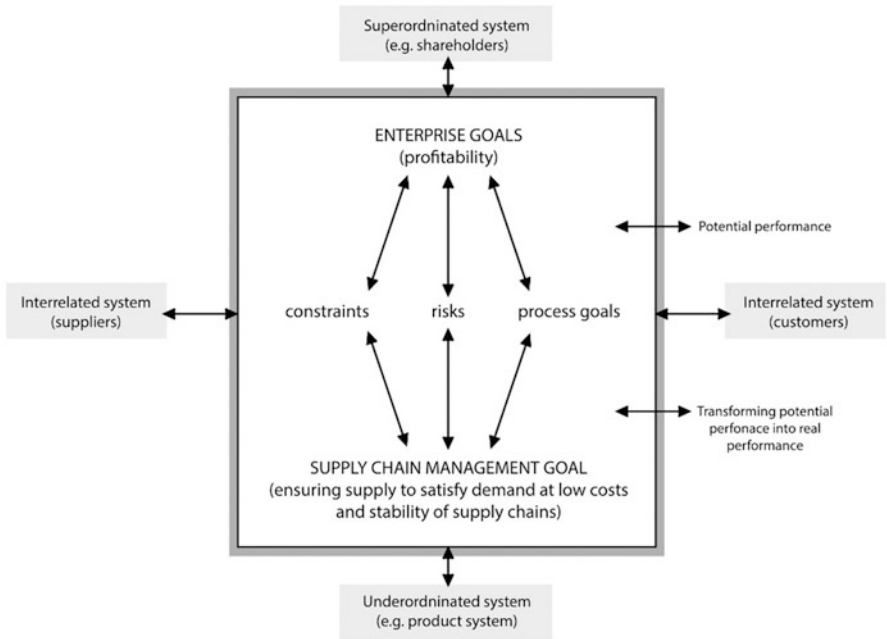


Fig. 1.4 Supply chain management as a system (Based on Ivanov and Sokolov 2010)

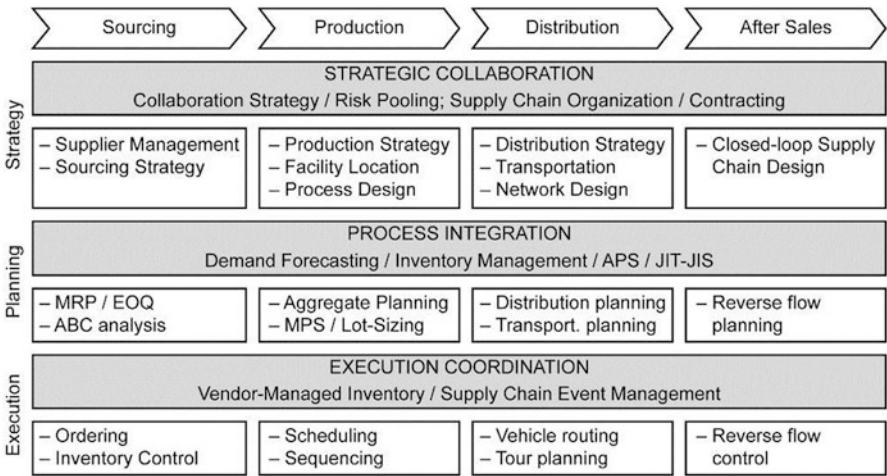


Fig. 1.5 Decision matrix in supply chain management (Ivanov et al. 2017)

Strategic issues include, for example, determination of the size and location of manufacturing plants or distribution centres, decisions about the structure of service networks, factory planning, and designing the supply chain. *Tactical* issues include such decisions as production or transportation planning as well as inventory

planning. *Operative* issues involve production scheduling and control, inventory control, quality control and inspection, vehicle routing, traffic and materials handling, and equipment maintenance policies.

This description holds true for many different organizations such as global brand manufacturers, Apple or Toyota, major retailers such as Tesco or Wal-Mart, non-profit organizations such as International Red Cross, local petrol stations or hospitals. Purchasing, assembly, shipping, stocking and even communicating are just a few examples of the many different actions unfolding within these organizations, united by a single purpose: to *create value for a customer*.

Only a few years have passed since supply chain management was considered as an extension of logistics and purchasing management. Modern supply chain management is a wider concept than just logistics. Supply chain management has been extensively developed into an independent research and management domain. For the last few years, the focus of supply chain management has shifted to the management level. Organization, strategies, planning and control at different decision-making levels are the subjects of management science. To implement the managerial functions, information and engineering technologies are needed. In fact, the level of the existing technologies enables or disables management concepts. Hence, supply chain management should be considered as a *multi-disciplinary framework* of management science, engineering science and information science.

In this book, we consider supply chains from the above-mentioned point of view. The research principles of structural dynamics control, adaptive control, and multi-disciplinary modelling will be applied to approach handling complexity, uncertainty, and operations dynamics in supply chains. Special consideration will be given to the aspects of supply chain dynamics at the strategic, tactical and operative decision levels.

1.3 Technical Description of Supply Chain Structural Dynamics

Let us introduce the following basic sets and structures (based on Ivanov and Sokolov 2010):

$B = \{B^{(j)}, j \in N = \{1, \dots, n\}\}$ is a set of internal objects, e.g. enterprises that are embodied in a supply chain and are necessary for its operation;

$\bar{B} = \{\bar{B}^{(i)}, i \in \bar{N} = \{1, \dots, \bar{n}\}\}$ is a set of external objects (customers, shareholders, creditors, logistics service providers) interacting with the supply chain (the interaction may be informational, financial or material);

$\tilde{B} = B \cup \bar{B}$ is a set of objects in the supply chain design;

$\tilde{C} = C \cup \bar{C} = \{C_1, C_2, \dots, C_n\} \cup \{\bar{C}_1, \bar{C}_2, \dots, \bar{C}_{\bar{n}}\}$ is a set of channels that are used for informational interaction;

$D = \left\{ D_{\mu}^{(i)}, \mu \in K_i^{(o)} = \{1, \dots, s_i\}, i = 1, \dots, \bar{n} \right\}$ is a set of interaction operations with the object $B^{(i)}$;
 $\Phi R = \left\{ \left\{ \Phi S_{\pi}^{(j)} \right\} \cup \left\{ \Phi N_{\pi'}^{(j)} \right\}, j \in N, \pi \in K_j^{(p,1)} = \{1, \dots, k_j^{(p,1)}\}, \pi' \in K_j^{(p,2)} = \{1, \dots, k_j^{(p,2)}\} \right\}$ is a set of supply chain resources;
 $\Phi S^{(j)} = \left\{ \Phi S_{\pi}^{(j)}, \pi \in K_j^{(p,1)} \right\}$ is a set of non-storable resources (time) of the object $B^{(j)}$;
 $\Phi N^{(j)} = \left\{ \Phi N_{\pi'}^{(j)}, \pi' \in K_j^{(p,2)} \right\}$ is a set of storable resources (materials) of the object $B^{(j)}$;
 $P = \left\{ \left\{ P_{\langle \bar{\mu}, \bar{\rho} \rangle}^{(j)} \right\} \cup \left\{ P_{\langle \bar{\mu}, \bar{\rho} \rangle}^{(i,j)} \right\} \right\}$ is a set of supply chain flows that are under consumption for different resources (financial flows, material flows and information flows);
 $P^{(j)} = \left\{ \left\{ P_{\langle \bar{\mu}, \bar{\rho} \rangle}^{(j)} \right\}, j \in N, \bar{\mu} \in \tilde{K}_i^{(o)} = \{1, \dots, \bar{s}_i\}, \bar{\rho} \in \tilde{K}_i^{(f)} = \{1, \dots, \bar{p}_i\} \right\}$ is a set of flows produced by or necessary for the object $B^{(j)}$;
 $P^{(i,j)} = \left\{ \left\{ P_{\langle \mu, \rho \rangle}^{(i,j)} \right\}, i \in \bar{N}, j \in N, \mu \in K_i^{(o)} = \{1, \dots, s_i\}, \rho \in K_i^{(f)} = \{1, \dots, p_i\} \right\}$ is a set of flows (informational, financial or material) produced when the objects $B^{(i)}$ and $B^{(j)}$ interact.

Let $G = \{ G_{\chi}, \chi \in NS \}$ be the set of structures that are being formed within the supply chain. To interconnect the structures let us consider the following *dynamic alternative multigraph* (Eq. 1.1):

$$G_{\chi}^t = \left\langle X_{\chi}^t, F_{\chi}^t, Z_{\chi}^t \right\rangle, \quad (1.1)$$

where the subscript χ characterizes the supply chain design structure type, $\chi \in NS = \{1, 2, 3, 4, 5, 6\}$, the time point t belongs to a given set T ; $X_{\chi}^t = \left\{ x_{\langle \chi, l \rangle}^t, l \in L_{\chi} \right\}$ is a set of elements of the structure G_{χ}^t (the set of dynamic alternative multigraph vertices) at the time point t ; $F_{\chi}^t = \left\{ f_{\langle \chi, l, l' \rangle}^t, l, l' \in L_{\chi} \right\}$ is a set of arcs of the dynamic alternative multigraph G_{χ}^t and represent relations between the dynamic alternative multigraph elements at time t ; $Z_{\chi}^t = \left\{ z_{\langle \chi, l, l' \rangle}^t, l, l' \in L_{\chi} \right\}$ is a set of parameters that characterize relations numerically.

The graphs of different types are interdependent thus, for each operation, the following maps should be constructed (Eq. 1.2):

$$MM_{\langle \chi, \chi' \rangle}^t : F_{\chi}^t \rightarrow F_{\chi'}^t. \quad (1.2)$$

Composition of the maps can be also used at time t as shown in Eq. (1.3):

$$MM_{\langle \chi, \chi' \rangle}^t = MM_{\langle \chi, \chi_1 \rangle}^t \circ MM_{\langle \chi_1, \chi_2 \rangle}^t \circ \dots \circ MM_{\langle \chi'', \chi' \rangle}^t. \quad (1.3)$$

A multi-structural state can be defined as the following inclusion (Eq. 1.4):

$$S_\delta \subseteq X_1^t \times X_2^t \times X_3^t \times X_4^t \times X_5^t \times X_6^t, \quad \delta = 1, \dots, K_\sigma. \quad (1.4)$$

Now we obtain the set of the supply chain multi-structural macro-states in dynamics (Eq. 1.5):

$$S = \{S_\delta\} = \{S_1, \dots, S_{K_\sigma}\}. \quad (1.5)$$

Allowable transitions from one multi-structural state to another one can be expressed by means of the maps as shown in Eq. (1.6):

$$\Pi_{<\delta, \delta'>}^t : S_\delta \rightarrow S_{\delta'}. \quad (1.6)$$

Here we assume that each multi-structural state at time $t \in T$ is defined by a composition (Eq. 1.6).

Now, the problem of supply chain with supply chain design considerations can be regarded as a selection of multi-structural macro-states $S_\delta^* \in \{S_1, S_2, \dots, S_{K_\sigma}\}$ and transition sequence (composition) $\Pi_{<\delta_1, \delta_2>}^{t_1} \circ \Pi_{<\delta_2, \delta_3>}^{t_2} \circ \dots \circ \Pi_{<\delta', \delta>}^{T_f}$ ($t_1 < t_2 < \dots < T_f$), under some criteria of effectiveness, e.g. service level and costs.

Dynamics of the supply chain execution are presented as a dynamic alternative multigraph in order to relate the above sets and structures. The dynamic alternative multigraph is characterized by multi-structural macro-states. The dynamic alternative multigraph and the multi-structural macro-states have been developed to meet the requirements on multi-structural design and to link planning and execution models, taking into account the structure dynamics.

In integrating the operation dynamics model and the supply chain design model, the following general model construction can be presented (Eqs. 1.7 and 1.8). The goal is to find such $<U_*^t, S_\delta^{*T_f}>$ on the following constraints:

$$J_\zeta \left(X_\chi^t, F_\chi^t, Z_\chi^t, MM_{<\chi, \chi'>}^t, \Pi_{<\bar{\delta}, \bar{\delta}>}^t, t \in (T_0, T_f] \right) \rightarrow_{<U^t, S_\delta^{*T_f}> \in \Delta^{(d)} \cup \Delta^{(s)}} extr, \quad (1.7)$$

$$\Delta^{(d)} \cup \Delta^{(s)} = \left\{ <U^t, S_\delta^{T_f}> \left| R_{\bar{r}} \left(X_\chi^t, F_\chi^t, Z_\chi^t, MM_{<\chi, \chi'>}^t, \Pi_{<\bar{\delta}, \bar{\delta}>}^t \right) \leq \tilde{R}_{\bar{r}}; \right. \right. \\ \left. \left. U^t = \Pi_{<\delta_1, \delta_2>}^{t_1} \circ \Pi_{<\delta_2, \delta_3>}^{t_2} \circ \dots \circ \Pi_{<\bar{\delta}, \delta>}^{t_2} \right\}, \quad (1.8)$$

where U^t are control actions for synthesis, J_ζ are supply chain performance metrics (costs, service level, etc.), $\zeta \in \{1, \dots, \mathcal{J}\}$ is a set of the performance metric numbers, $\Delta^{(d)} \cup \Delta^{(s)}$ is a set of dynamic and static alternatives of supply chains, $\bar{r} \in \{1, \dots, \tilde{R}\}$ is a set of business and information processes constraints numbers, $R_{\bar{r}}$ is a set business and information processes constraints; $\tilde{R}_{\bar{r}}$ are constants, which are known and $T = (T_0, T_f]$ is interval of time for supply chain synthesis. Other symbols have been explained above.

1.4 General Formal Statement of the Supply Chain Structure Dynamics Control Problem

Let us consider the generalized formal statement of the supply chain design problem. This statement is introduced to work out in detail the description given in Eqs. (1.7 and 1.8). First, we introduce basic sets and vectors (Eq. 1.9). The formulas define a dynamic system describing supply chain design processes. Here, $\mathbf{x}(t)$ is a general state vector of the supply chain and $\mathbf{y}(t)$ is a general vector of output characteristics. $\mathbf{u}(t)$ and $\mathbf{v}(\mathbf{x}(t), t)$ are control vectors. $\mathbf{u}(t)$ represents the supply chain control programmes (plans of supply chain functioning) and $\mathbf{v}(\mathbf{x}(t), t)$ is a vector of control inputs compensating for perturbation impacts $\xi(t)$. The vector β is a general vector of supply chain parameters. The subscripts define the types of models M .

$$\begin{aligned}
 \mathbf{x}(t) &= \left\| \mathbf{x}^{(g)T}(t), \mathbf{x}^{(k)T}(t), \mathbf{x}^{(o)T}(t), \mathbf{x}^{(p)T}(t), \right. \\
 &\quad \left. \mathbf{x}^{(f)T}(t), \mathbf{x}^{(e)T}(t), \mathbf{x}^{(c)T}(t), \mathbf{x}^{(\nu)T}(t) \right\|^T, \\
 \mathbf{y}(t) &= \left\| \mathbf{y}^{(g)T}(t), \mathbf{y}^{(k)T}(t), \mathbf{y}^{(o)T}(t), \mathbf{y}^{(p)T}(t), \right. \\
 &\quad \left. \mathbf{y}^{(f)T}(t), \mathbf{y}^{(e)T}(t), \mathbf{y}^{(c)T}(t), \mathbf{y}^{(\nu)T}(t) \right\|^T, \\
 \mathbf{u}(t) &= \left\| \mathbf{u}^{(g)T}(t), \mathbf{u}^{(k)T}(t), \mathbf{u}^{(o)T}(t), \mathbf{u}^{(p)T}(t), \right. \\
 &\quad \left. \mathbf{u}^{(f)T}(t), \mathbf{u}^{(e)T}(t), \mathbf{u}^{(c)T}(t), \mathbf{u}^{(\nu)T}(t) \right\|^T, \\
 \xi(t) &= \left\| \xi^{(g)T}(t), \xi^{(k)T}(t), \xi^{(o)T}(t), \xi^{(p)T}(t), \right. \\
 &\quad \left. \xi^{(f)T}(t), \xi^{(e)T}(t), \xi^{(c)T}(t), \xi^{(\nu)T}(t) \right\|^T, \\
 \beta &= \left\| \beta^{(g)T}, \beta^{(k)T}, \beta^{(o)T}, \beta^{(p)T}, \beta^{(f)T}, \beta^{(e)T}, \beta^{(c)T}, \beta^{(\nu)T} \right\|^T.
 \end{aligned} \tag{1.9}$$

We consider the following models:

- M_g – dynamic model of transportation control in the supply chain
- M_k – dynamic model of supply chain channel control
- M_o – dynamic model of supply chain operations control
- M_f – dynamic model of supply chain flow control
- M_p – dynamic model of supply chain resource control
- M_e – dynamic model of supply chain operation parameters control
- M_c – dynamic model of supply chain structural dynamics control
- M_ν – dynamic model of supply chain auxiliary operation control

All the described vectors should meet space–time, technical, and technological limitations; in other words, the vectors should belong to given sets (Eqs. 1.10, 1.11, and 1.12):

$$\mathbf{u}(t) = \left\| \mathbf{u}_{pl}^T(t), \mathbf{v}^T(\mathbf{x}(t), t) \right\|^T; \quad \mathbf{u}_{pl}(t) \in \mathbf{Q}(\mathbf{x}(t), t); \quad \mathbf{v}(\mathbf{x}(t), t) \in \mathbf{V}(\mathbf{x}(t), t), \tag{1.10}$$

$$\xi(t) \in \Xi(\mathbf{x}(t), t); \quad \boldsymbol{\beta} \in \tilde{B}, \quad (1.11)$$

$$\mathbf{x}(t) \in \mathbf{X}(\xi(t), t), \quad (1.12)$$

where $\mathbf{Q}(\mathbf{x}(t), t)$, $\mathbf{V}(\mathbf{x}(t), t)$ and $\Xi(\mathbf{x}(t), t)$ are correspondingly allowable areas for programme control, real-time regulation control inputs and perturbation inputs, $\tilde{B}$ is an area of allowable values of parameters and $\mathbf{X}(\xi(t), t)$ is an area of allowable states of supply chain design. The dynamics of state and output vectors can be described by means of a transition function and an output one (Eqs. 1.13 and 1.14):

$$\mathbf{x}(t) = \tilde{\varphi}(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t), \quad (1.13)$$

$$\mathbf{y}(t) = \tilde{\psi}(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t). \quad (1.14)$$

The transition function $\tilde{\varphi}(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t)$ and the output function $\tilde{\psi}(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t)$ can be defined in an analytical or algorithmic form. Analytical derivations can be found in the study by Ivanov et al. (2016).

There are additional constraints for the initial state and the final state (Eq. 1.15):

$$\mathbf{x}(T_0) \in \mathbf{X}_0(\boldsymbol{\beta}), \mathbf{x}(T_f) \in \mathbf{X}_f(\boldsymbol{\beta}). \quad (1.15)$$

Equation (1.15) determines the end conditions for the supply chain state vector $\mathbf{x}(t)$ at time $t = T_0$ and $t = T_f$ (T_0 is the initial time of the time interval in which the supply chain is being investigated, and T_f is the final time of the interval).

Let us introduce the following vector of the *multi-model quality functional* (total performance metric) to evaluate the supply chain performance in the operation period (Eq. 1.16):

$$\mathbf{J}_\Theta(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t) = \left\| \mathbf{J}^{(g)\text{T}}, \mathbf{J}^{(k)\text{T}}, \mathbf{J}^{(o)\text{T}}, \mathbf{J}^{(p)\text{T}}, \mathbf{J}^{(f)\text{T}}, \mathbf{J}^{(e)\text{T}}, \mathbf{J}^{(c)\text{T}}, \mathbf{J}^{(u)\text{T}} \right\|^{\text{T}}. \quad (1.16)$$

The problem of supply chain design includes tasks of three main classes.

Class A problems (problems of structured analysis, problems of supply chain structure dynamics analysis with or without perturbation impacts); *for constraints* (Eqs. 1.10, 1.11, 1.12, 1.13, 1.14, and 1.15), $t \in (T_0, T_f]$ it is necessary to obtain $\mathbf{x}(t)$, $\mathbf{y}(t)$, $J_G(t)$, where $J_G(t)$ is the generalized performance metric which is constructed by multi-criteria procedures.

Class B problems (estimation (observation) of problems, monitoring problems, problems of supply chain structural state identification); *for constraints* (Eqs. 1.10, 1.11, 1.12, 1.13, 1.14, and 1.15), $\mathbf{y}(\hat{t})$, $\hat{t} \in (T_0, T_f]$ it is necessary to obtain structural state estimation $\hat{\mathbf{x}}(\hat{t})$ and structure parameters estimations $\hat{\boldsymbol{\beta}}$; here $\hat{t}$, $t \in (T_0, T_f]$.

Class C problems (problems of control input selection and problems of supply chain parameter selection, i.e. multi-criteria control problems for supply chain structures, modes and parameters, and multi-criteria problems of supply chain

structural–functional synthesis); *for constraints* (Eqs. 1.10, 1.11, 1.12, 1.13, 1.14, and 1.15), $t \in (T_0, T_f]$ and performance metrics in Eq. (1.16) it is necessary to obtain $\mathbf{u}_{pl}(t)$, $\mathbf{v}(\mathbf{x}(t), t)$, $\boldsymbol{\beta}$ such that the generalized functional $J_G = J_G(\mathbf{J}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(x(t), t), \boldsymbol{\xi}(t)))$ possesses its extreme values.

1.5 Generalized Dynamic Model of Supply Chain Structural Dynamics Control Processes (M Model)

In this section, interconnection scheme of supply chain control models is presented. This generalized model provides a unified technology for an analysis and optimization of various processes concerning supply chain design, planning and execution.

The detailed mathematical formulation of these models has been presented by Kalinin and Sokolov (1985, 1987), Okhtilev et al. (2006), and Ivanov and Sokolov (2010). Here let us provide the generalized dynamic model of supply chain structural dynamics control processes (M model) (Eqs. 1.17 and 1.18):

$$\begin{aligned} M = \{ & \mathbf{u}(t) | \mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t); \mathbf{h}_0(\mathbf{x}(T_0)) \leq \mathbf{O}, \\ & \mathbf{h}_1(\mathbf{x}(T_f)) \leq \mathbf{O}, \mathbf{q}^{(1)}(\mathbf{x}, \mathbf{u}) = \mathbf{O}, \mathbf{q}^{(2)}(\mathbf{x}, \mathbf{u}) < \mathbf{O} \}, \end{aligned} \quad (1.17)$$

$$\begin{aligned} J_{\vartheta} = J_{\vartheta}(\mathbf{x}(t), \mathbf{u}(t), t) = & \varphi_{\vartheta}(\mathbf{x}(t_f)) + \int_{T_0}^{T_f} f_{\vartheta}(\mathbf{x}(\tau), \mathbf{u}(\tau), \tau) d\tau, \\ & \vartheta \in \{g, k, o, f, p, e, c, \nu\}, \end{aligned} \quad (1.18)$$

where $\mathbf{x} = \|\mathbf{x}^{(g)T}, \mathbf{x}^{(k)T}, \mathbf{x}^{(o)T}, \mathbf{x}^{(p)T}, \mathbf{x}^{(f)T}, \mathbf{x}^{(e)T}, \mathbf{x}^{(c)T}, \mathbf{x}^{(\nu)T}\|^T$ is a vector of the supply chain generalized state, $\mathbf{u} = \|\mathbf{u}^{(g)T}, \mathbf{u}^{(k)T}, \mathbf{u}^{(o)T}, \mathbf{u}^{(p)T}, \mathbf{u}^{(f)T}, \mathbf{u}^{(e)T}, \mathbf{u}^{(c)T}, \mathbf{u}^{(\nu)T}\|^T$ is a vector of the generalized control, $\mathbf{h}_0, \mathbf{h}_1$ are known vector functions that are used for the state $\mathbf{x}$ end conditions at the time points $t = T_0$ and $t = T_f$, and the vector functions $\mathbf{q}^{(1)}, \mathbf{q}^{(2)}$ define the main spatio–temporal, technical and technological conditions for the supply chain execution.

On the whole the constructed model M (Eq. 1.17) is a deterministic non-linear non-stationary finite-dimensional differential system with a reconfigurable structure. Figure 1.6 extends the model Eqs. (1.17 and 1.18) by incorporating uncertainty via perturbation functions and shows the interconnection of models $M_g, M_k, M_o, M_p, M_f, M_e, M_c$ and M_{ν} embedded in the generalized model.

In Fig. 1.6, the additional vector function of perturbation influences $\boldsymbol{\xi} = \|\boldsymbol{\xi}^{(g)T}, \boldsymbol{\xi}^{(k)T}, \boldsymbol{\xi}^{(o)T}, \boldsymbol{\xi}^{(p)T}, \boldsymbol{\xi}^{(f)T}, \boldsymbol{\xi}^{(e)T}, \boldsymbol{\xi}^{(c)T}, \boldsymbol{\xi}^{(\nu)T}\|^T$ is introduced. This function describes the impact of the environment upon the supply chain operation.

The solutions obtained in the multi-model complex presented are coordinated by the control inputs vector $\mathbf{u}^{(o)}(t)$ of the model M_o . This vector determines the sequence of interaction operations and fixes the supply chain resource allocation and coordination.

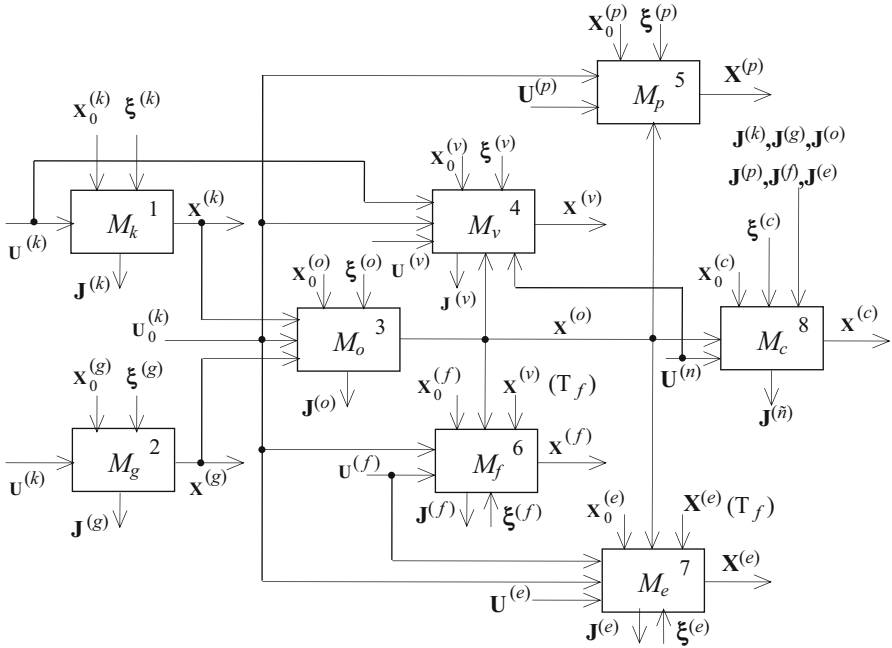


Fig. 1.6 The scheme of model interconnection

The model complex M evolves and generalizes the dynamic models of supply chain structural dynamics control (Sokolov and Yusupov 2004; Ivanov and Sokolov 2012). The main distinctive feature of the complex is that non-linear technological constraints are actualized in the convex domain of allowable control inputs rather than in differential equations (Ivanov and Sokolov 2010).

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Chapter 2

Supply Chain Risk Management: Bullwhip Effect and Ripple Effect

2.1 Uncertainty and Risks

Uncertainty is a system property characterizing the incompleteness of our knowledge about the system and the conditions of its development. Uncertainty is a polysemic term (poly – many, sema – a sign). Historically, the first terms related to uncertainty were accident, probability and possibility, which we relate to Aristotle. Up to the twentieth century, the mathematical basics of uncertainty factor description were founded on probability–frequency interpretation and are related to Pascal, Ferma, Bernoulli and Laplace. Modern probability theory is based on the research of Kolmogorov, who introduced an axiomatic definition of probability as a measure related to a system of axioms of a so-called probability space.

In contrast to risk, uncertainty is a more comprehensive term, considering situations that cause both positive (chance) and negative (threats) deviations from an expected outcome. Modern system theory defines uncertainty as “a gradual assessment of the truth content of a proposition, e.g. in relation to the occurrence of the event” (Möller and Beer 2004).

One of the main dangers of uncertainty is the perturbation impacts, leading to a change in a planned course of events in the supply chain functioning and (or) a threat of economic performance decrease such as lost sales or stock returns. There are different external and internal, objective and subjective perturbation impacts altering the execution conditions of a supply chain.

Let us analyse the main types of perturbation influences that can be divided into two groups:

- purposeful perturbation influences; and
- non-purposeful perturbation influences.

Purposeful perturbation influences can be antagonistic (impeding supply chain functioning) or non-antagonistic (promoting supply chain functioning). Examples

of purposeful perturbation impacts are thefts, terrorism, piracy and financial misdeeds.

Non-purposeful perturbation influences can be natural, economic or technological. The former can be caused by phenomena of the geo-, hydro- or biosphere. Examples of an economic non-purposeful perturbation impact are demand fluctuations and the bullwhip-effect.

Hence, there are two types of uncertainty affecting supply chains: (1) risks arising from the problems of coordinating supply and demand and (2) risks arising from purposeful disruptions to normal activities (Kleindorfer and Saad 2005).

2.1.1 Sources of Uncertainty

In Fig. 2.1, a classification of uncertainty origins is undertaken.

Research on how to cope with disturbances has mostly been concentrated on the *environmental uncertainty* (i.e. demand fluctuations and the so-called bullwhip-effect) (Chen et al. 2000; Lee et al. 1997) by means of stochastic or robust optimization. Other research streams deal with uncertainty caused by *human decisions* and goals. Sterman (1989) sees wrong decisions made by human decision makers as the major cause of the bullwhip effect. Hallikas et al. (2004) considered organizational risks and proposed an approach to reduce uncertainty by means of increasing entire network transparency. Sokolov and Yusupov (2006) distinguished seven psychological types of managers and considered this criterion in the model of risk management.

Uncertainty factors are usually divided into two groups: stochastic factors and non-stochastic factors. The first group can be described via probability models. The factors described as aleatory variables (functions, fields) with known distributions are statistically defined. Aleatory variables with unknown distributions can be of two types: those with known or unknown characteristics. The following factors produce non-stochastic uncertainty:

- Purposeful opposition of a rival system, while its actions are unknown. This type of uncertainty is called behavioural.
- Phenomena interrelated with supply chain operation and insufficiently studied. This type of uncertainty is called uncertainty of nature.
- Uncertainty of human thinking. This kind of uncertainty arises when the system is being managed or investigated. It can be called personnel uncertainty.
- Uncertainty of knowledge in the system of artificial intellect.

For the formal description of non-stochastic uncertainty, fuzzy description with known membership functions, subjective probabilities for the uncertainty factors, interval description, and combined description of the uncertainty factors are used.

In analysing uncertainty, four aspects are usually encountered. The first is uncertainty itself, the second is risks, the third is perturbation influence (disturbances), and the last is the perturbation impact influences (deviations). In the further

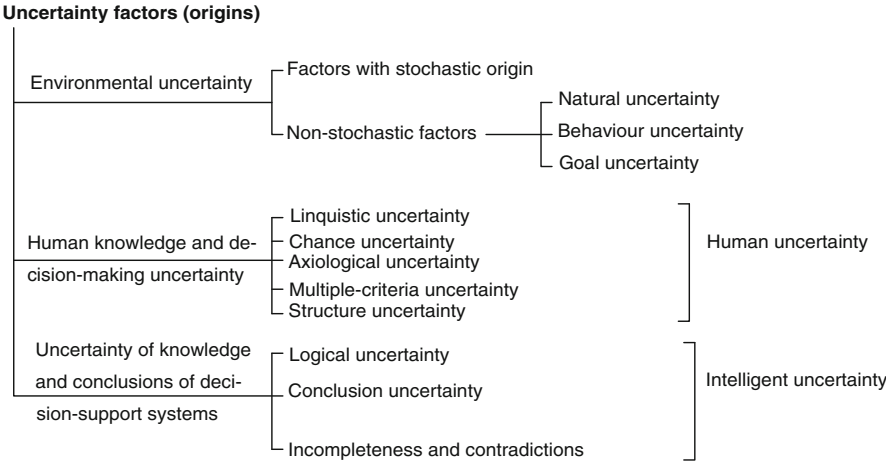


Fig. 2.1 Classification of uncertainty factors (Ivanov and Sokolov 2010)

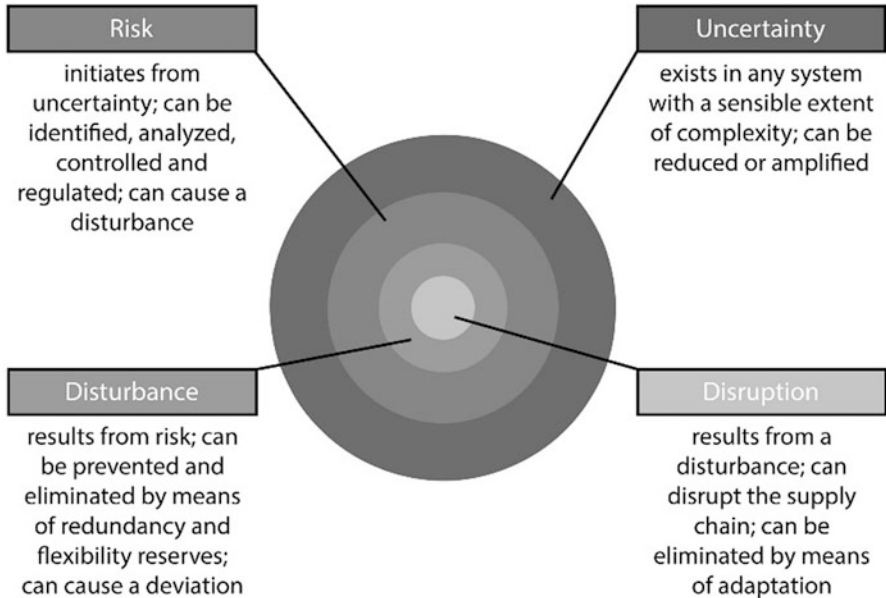


Fig. 2.2 Interrelations of uncertainty, risk, disturbance and disruption (Based on Ivanov and Sokolov 2010)

course of this and the following chapters, we will frequently encounter this constellation (see Fig. 2.2).

Uncertainty is the general property of a system environment that exists independent of us for any system of a sensible complexity degree. As shown in Fig. 2.2, we can broaden and narrow the uncertainty space.

Table 2.1 Uncertainty factors and measures for their handling in supply chains

Decision-making level	Uncertainty factors	Handling measures
Strategic	Multiple management goals Terrorism, piracy Financial and political crises Natural disasters	Multi-criteria analysis techniques Supply chain security management Liquid assets reserves Strategic material inventories Market diversification and outsourcing Product lines' flexibility and modularity
Tactical and operational	Weak coordination Stockless processes Weak control of cargo security Technological breaks Human errors	Safety stocks and time buffers Reserves of supply chain capacities Supply chain coordination, monitoring, and event management

Risk arises from uncertainty. Risks can be identified, analysed, controlled and regulated. We consciously talked about uncertainty factors and the appearance of risks such as the risk of demand fluctuation as a result of the environmental uncertainty.

A *disturbance* (perturbation impact) is the consequence of risks. It may be purposeful (i.e. thefts) and non-purposeful (i.e. demand fluctuations or the occurrence of some events that may necessitate adapting the supply chain). It may cause a deviation (disruption) in the supply chain or not (e.g. a supply chain can be robust and adaptive enough to overcome the disturbance).

Operational *deviations* (or severe *disruptions*) are the result of perturbation influences. They may affect operations, processes, plans, goals or strategies. To adjust the supply chain in the case of deviations, adaptation measures need to be taken.

For the supply chain management domain, uncertainty factors and measures for their handling can be distinguished as follows (see Table 2.1).

In Table 2.2, some examples of disturbances and disruptions in supply chains in recent years are presented.

A survey by the Business Continuity Institute (2011) found that 85% of companies with global supply chains had experienced at least one supply chain disruption in the previous 12 months. The authors from the same institute found in a later survey (Alcantara and Riglietti 2015) that 74% of firms had experienced more than one supply chain disruption, with 6–20 disruptions per year for 15% of the companies. The costs of such disruption can be high, leading to lower revenue, increased downtime, delays in delivery, lost customers, stock return decrease and damaged reputations (Hendricks and Singhal 2005).

2.1.2 Uncertainty and Complexity

Complexity has been one of the most challenging phenomena in business and science over the last 60 years (Ashby 1956; Simon 1962; Bertalanffy 1968; Mesarovic and Takahara 1975; Casti 1979; Holland 1995; Anderson 1999;

Table 2.2 Examples of disturbances and disruptions in supply chains (Extended from Ivanov and Sokolov 2010)

Factor	Example	Impacts
Terrorism Piracy	September 11 Somali, 2008	Five Ford plants have been closed for a long time Breaks in many supply chains
Natural disasters	Earthquake in Thailand, 1999 Flood in Saxony, 2002 Earthquake in Japan, 2007	Apple computers' production in Asia has been paralysed Significant production decrease at VW, Dresden Production breakdown in Toyota's supply chains amounted to 55,000 cars
	Hurricane Katrina, 2006	This storm halted 10–15% of total US gasoline production, raising both domestic and overseas oil prices
	Earthquake and tsunami in Japan, 2011	Massive collapses in global automotive and electronics supply chains; Toyota lost its market leadership position
	Floods in Chennai, India in 2015	Production of academic literature has been stopped at many international publishing houses
Man-made disasters	Explosion at BASF plant in Ludwigshafen in 2016	15% of raw materials were missing for the entire supply chain Production of some products at BASF has been stopped for many weeks
	Fire at distribution centre of e-commerce retail company ASOS in 2005	Delivery stop for a month
	A fire in the Phillips semiconductor plant in Albuquerque, New Mexico in 2000	Phillips's major customer, Ericsson, lost \$400 million in potential revenue
Political crises	"Gas" crisis 2009	Breaks in gas supply from Russia to Europe, billions of losses to GAZPROM and customers
Financial crises	Autumn 2008	Production decrease or closing; breaks in supply chains throughout
Strikes	Strikes at Hyundai plants in 2016	Production of 130,000 cars has been affected
Legal contract disputes	Volkswagen and Prentiss Group contract dispute in summer 2016	Six German factories face production halt on parts shortage; 27,700 workers are affected, with some sent home and others moved to short-time working

Lissak and Letiche 2002; Richardson 2004, 2005, 2007; Pathak et al. 2007). Complexity is a multi-spectral category and one of the basic properties of systems of any nature (see Sect. 5.3).

The fulfilled analysis confirmed that a well-founded concept for uncertainty analysis in the supply chain models is a system-cybernetics one (see Fig. 2.3).

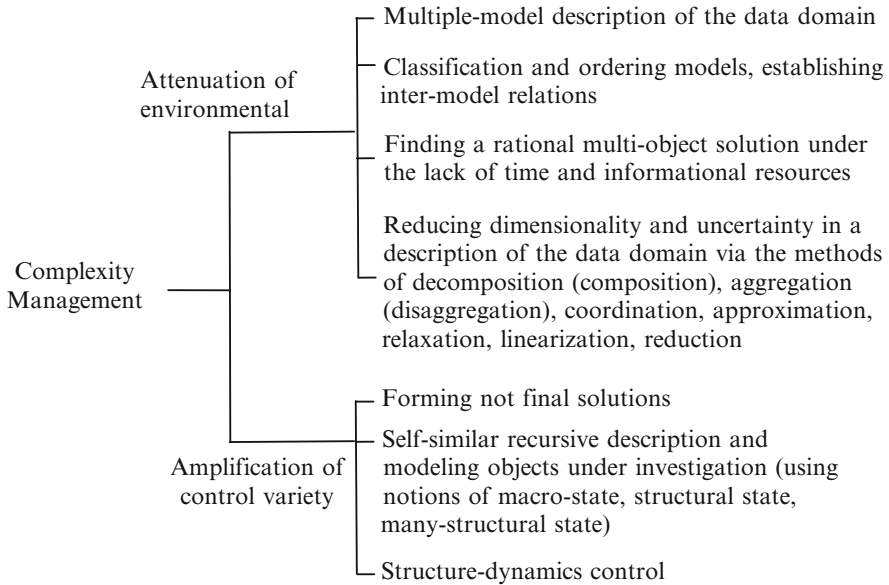


Fig. 2.3 Directions for realizing the law of requisite variety

This concept assumes that all the input signals of a dynamic system (supply chain, in our case) can be divided into two classes: control inputs and perturbation inputs. Moreover, it is assumed that the control inputs are known, and thus the supply chain and its control processes can be regarded as deterministic mathematical constructions. All of the perturbation factors are called factors of uncertainty. They belong to the environment into which the deterministic object is “plunged”.

Complexity management and system modelling can be considered as a theoretical basis for handling uncertainty in supply chains. From the perspective of complexity management, the problem of a system under control and uncertainty is related to an area under control and an area under uncertainty. This idea is based on Ashby’s principle (Ashby 1956) of requisite variety (Fig. 2.4).

By broadening the control area (Fig. 2.4b) and narrowing the uncertainty area or reverse (Fig. 2.4a), the system control can be adapted. Hence, the mutual relations between the system and environment spaces fall into the categories of amplification of a *control variety* and attenuation of an *environmental variety* (see Fig. 2.4). Thus, amplifying the variety of our control area and reducing the area of uncertainty, (1) a balance of control and perturbed impacts as well as (2) the maintenance of the planned execution processes and a quick cost-efficient process recovery once disturbed can be reached.

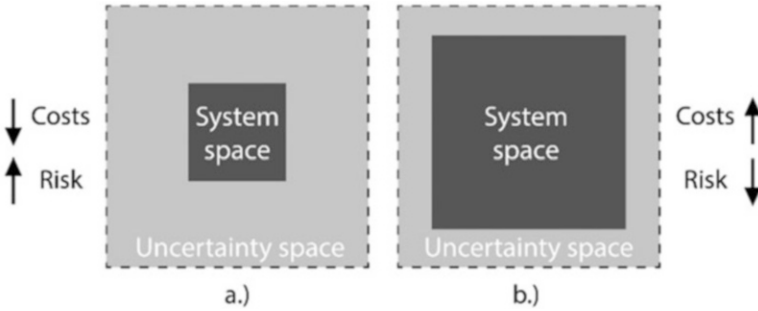


Fig. 2.4 System space and uncertainty space

2.2 Risk Management in the Supply Chain

Risk management in the supply chain became one of the most important topics in research and practice over the last decade. A number of books (Handfield and McCormack 2008; Kouvelis and Dong 2011; Waters 2011; Gurnani et al. 2012; Heckmann 2016; Khojasteh 2017) and literature review papers (Klibi et al. 2010; Simangunsong et al. 2012; Ho et al. 2015; Fahimnia et al. 2015; Gupta et al. 2016) provide insightful overviews and introductions to different aspects of this exciting field.

Recent literature introduced different classifications of supply chain risks (Chopra and Sodhi 2004; Tang and Musa 2011; Ho et al. 2015). For example, Chopra and Sodhi (2004) categorised potential supply chain risks into nine categories: (a) Disruptions (e.g. natural disasters, terrorism, war, etc.), (b) Delays (e.g. inflexibility of supply source), (c) Systems (e.g. information infrastructure breakdown), (d) Forecast (e.g. inaccurate forecast, bullwhip effect, etc.), (e) Intellectual property (e.g. vertical integration), (f) Procurement (e.g. exchange rate risk), (g) Receivables (e.g. number of customers), (h) Inventory (e.g. inventory holding cost, demand and supply uncertainty, etc.), and (i) Capacity (e.g. cost of capacity).

2.2.1 General Framework of Risk Control

Uncertainty initiates risk. At the stage of supply chain design (configuration and structure synthesis), uncertainty is a category that is mostly used in relation to risk management.

Risk management is a methodological approach to managing uncertainty outcome. The concept of risk is subject to various definitions. Knight (1921) classified under ‘risk’ the ‘measurable’ uncertainty. From the financial perspective of Markowitz (1952), risk is the variance of return. From a project management

perspective, risk is a measure of the probability and consequence of not achieving a defined project goal. According to March and Shapira (1987), risk is a product of the probability of occurrence of a negative event and the resulting amount of damage.

Generally, in decision theory, risk is a measure of the set of possible (negative) outcomes from a single rational decision and their probabilistic values. In the literature on supply chain management, the term “risk” is also replaced with “vulnerability”, which means “at risk”.

A particular feature of risk management in supply chains (unlike in technical systems) is that people do not strive for a *100% guarantee* of the result: they consciously tend to take risks. Some literature (e.g. Sokolov and Yusupov 2006) points out the problem of contradiction between *objective risks*, those determined by experts applying quantitative scientific means and *perceived risk*, those which include managers’ perceptions.

Actually, the objective risk treatment is rooted in technical science where 100% reliability is mandatory. In socio-economic systems, like supply chains, a value of 95% as an orientation for supply chains is empirically suggested (e.g. Sheffy 2005). Different managers perceive risk to different extents, and these perceptions can change in the same manager due to changes in his environment. That is why the models for supply chains should not strive for a unique optimal solution but allow the formation of a number of alternative solutions with different degrees of potential economic performance and risk. Summarizing, we will note that risk can be considered from three basic positions:

1. risk is a likelihood estimation of a negative outcome of the event leading to losses/losses (the technological approach);
2. risk is an individual estimation by the person of the danger of a negative outcome of the event leading to losses/losses; risk is ultimately a property of any entrepreneurship (the psychological approach);
3. risk is an integral property of any process or system, the management of which is a key problem in economic performance and stability maintenance (the organizational approach).

Let us describe the proposed concept of risk handling. In order to analyse risks, the following main categories are introduced: the risk factor, the risk source, the risk situation, and the dangerous situation. The risk factor is a global category that characterizes a system at the goal-orientation level (e.g. upsetting of the production plan, delivery breakdown, etc.). Risk sources consider certain events that may cause risk factors. The dangerous situation characterizes the state of a system when a probability of risk sources’ appearance and their direct influence on this system is high. The risk situation means a condition when the active influences of risk sources cause disturbances and deviations in system functioning (see Fig. 2.5).

The problem of supply chain functioning in terms of risk consists of the following main phases: risk factors’ identification → risk sources and dangerous situations’ identification → identification of interdependences between risk situation appearance and changes of system functioning parameters → decision-making

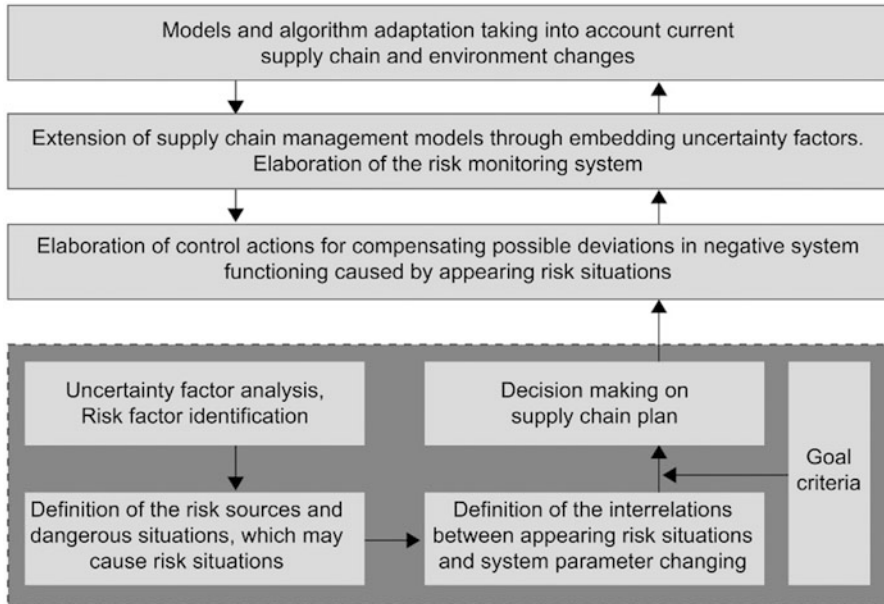


Fig. 2.5 Handling risks in supply chains

about compromise while supply chain configuration by aggravation of some goal criteria (e.g. cost increase while keeping the planned production volume and deadline; production volume reduction while keeping the same cost level and deadline; change of deadline while keeping the same costs and production volume, etc.) → control decision development in order to compensate for possible disturbances in system functioning caused by risk situations → development of a managed object monitoring system.

In summarizing the practical advancements in uncertainty handling within a supply chain environment, the following can be concluded:

1. Uncertainty space may be reduced by means of, e.g.:
 - introducing excessiveness in supply chain structures (e.g. time buffers, safety stocks, additional resources, capacity reserves, etc.);
 - improving coordination and information flows to make better quality, timeliness, and accessibility;
 - introducing supply chain monitoring and event management systems to react quickly to disturbances and disruptions; and
 - forming a set of not final decisions, i.e. postponement and rolling/adaptive planning.
2. It is impossible to avoid uncertainty.

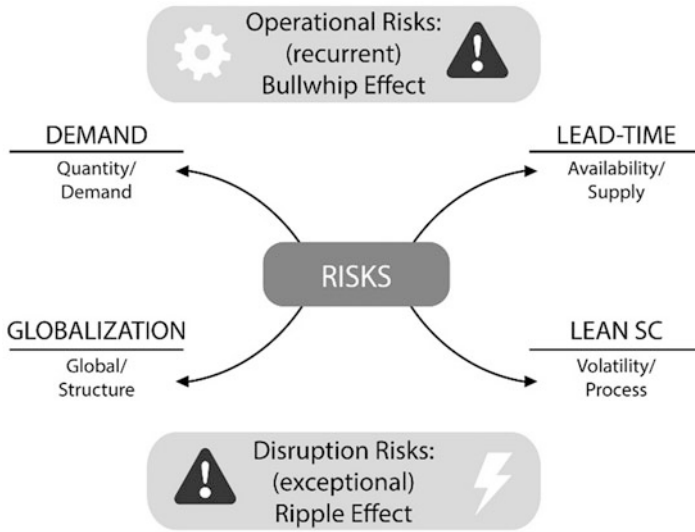


Fig. 2.6 Supply chain risks

2.2.2 Operational and Disruption Risks

The different types of risks in the supply chain can be classified into demand, supply, process, and structure areas (see Fig. 2.6).

Risks of demand and supply uncertainty are related to random uncertainty and business-as-usual situation. Such risks are also known as *recurrent* or *operational risks*. Supply chain managers achieved significant improvements at managing global supply chains and mitigating recurrent supply chain risks through improved planning and execution (Chopra and Sodhi 2014).

Disruption risks represent a new challenge for supply chain managers. First, globalization and outsourcing trends make supply chains more complex and less observable and controllable. According to complexity theory, such systems become more sensitive to disruptions. Special focus in this area is directed to disruptions in transportation channels. Second, the efficiency paradigms of lean processes, single sourcing, etc. have failed in disruption situations. As a consequence, supply chains became more vulnerable even to minor perturbations (Tsai 2016). Disruptions in a global supply chain, especially in its supply base, may immediately affect the entire supply chain. Third, with increased specialization and geographical concentration of manufacturing, disruptions in one or several nodes affect almost all the nodes and links in the supply chain. Fourth, IT became the crucial element of global supply chains, since disruptions in IT may have significant impacts on disruptions in material flows.

Recent literature and management practices provide evidence that it is mandatory to take into account uncertainty and risks in order to provide practically relevant problem statements and decision-oriented solutions. Recent literature

suggests considering *recurrent* or *operational* risks and *disruptive* risks (Chopra et al. 2007). Klibi et al. (2010) classify uncertainties and risks in the supply chain as follows:

- random uncertainty (demand fluctuation risks)
- hazard uncertainty (risk of unusual events with high impact)
- deep uncertainty (severe disruption risks)

For example, the risks of demand and lead-time uncertainty are related to random uncertainty and business-as-usual situations. Such risks are also known as *recurrent* or *operational risks* (Kleindorfer and Saad 2005; Chopra et al. 2007; Meisel and Bierwirth 2014; Aqlan and Lam 2015) and are frequently considered in the framework of the *bullwhip-effect* (Ouyang and Li 2010). Supply chain managers achieved significant improvements at managing supply chains and mitigating recurrent supply chain risks through improved coordinated planning and execution, e.g., vendor-managed inventory (VMI) or collaborative planning, forecasting and replenishment (CPFR) (Chopra and Sodhi 2014; Xu et al. 2015).

From 2000 thru 2017, supply chain disruptions (e.g., because of both natural and man-made disasters, such as on 11 March 2011 in Japan, floods in Thailand in 2011, fire in the Phillips Semiconductor plant in New Mexico, etc.) occurred in greater frequency and intensity, and thus with greater consequences (Chopra and Sodhi 2014; Simchi-Levi et al. 2014). Hendricks and Singhal (2005) quantified the negative effects of supply chain disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started 1 year before and ended 2 years after a disruption.

Disruption risks represent a new challenge for supply chain managers who face the *ripple effect* (Ivanov et al. 2014a, b, 2017b; Ivanov 2017; Dolgui et al. 2018) subject to *structural disruptions* in the supply chain, unlike the *parametrical deviations* in the bullwhip effect (Fig. 2.7).

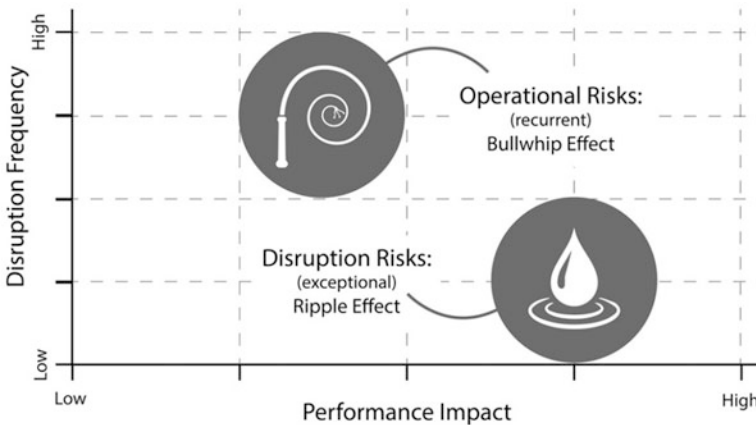


Fig. 2.7 Operational and disruption risks in supply chains

Table 2.3 Ripple effect and bullwhip effect

Feature	Ripple effect	Bullwhip effect
Risks	Disruptions (e.g. explosion)	Operative (e.g. demand fluctuation)
Affected areas	Structures and critical parameters (such as service level and total costs)	Operative parameters such as lead-time and inventory
Recovery	Middle- and long-term; significant coordination efforts and investments	Short-term coordination to balance demand and supply
Decreased performance	Output performance such as annual revenues	Mainly current performance such as daily/weekly stock-out/overage costs

In the last two decades, considerable advancements have been achieved in research regarding the mitigation of inventory and production shortages and response to demand fluctuations. In particular, the *bullwhip-effect* in the supply chain (supply chain) has been extensively considered in this domain subject to *randomness uncertainty* with the help of stochastic and simulation models.

However, deviations may also result from *hazard and deep uncertainty* (Klibi et al. 2010), and they have, therefore, different scope and scale. In recent years, the research community has started to investigate *severe supply chain disruptions* that can be caused, for example, by natural disasters, political conflicts, terrorism, maritime piracy, economic crises, destroying of information systems, or transport infrastructure failures.

The differences between the bullwhip effect and ripple effect are presented in Table 2.3.

The Bullwhip effect considers weekly/daily demand and lead-time fluctuations as primary drivers of the changes in the supply chain which occur at the parametric level and can be eliminated in a short-term perspective. In recent years, the research community has started to investigate severe supply chain disruptions with long-term impacts that can be caused, for example, by natural disasters, political conflicts, terrorism, maritime piracy, economic crises, destroying of information systems, or transport infrastructure failures. We refer to these severe natural and man-made disasters as the ripple effect in the supply chain where changes in the supply chain occur at the structural level and recovery may take mid- and long-term periods of time with significant impact on output performance such as annual revenues. In this setting, supply chain disruption management can be considered a critical capability which helps to create cost-efficient supply chain protection and implement appropriate actions to recover supply chain disruptions and performance.

Most studies on supply chain disruption consider how changes to some variables are rippling through the rest of the supply chain and impacting performance. Studies by Ivanov et al. (2014a, b) and Dolgui et al. (2018) suggest considering this situation as *the ripple effect in the supply chain*, as an analogy to computer science, where the ripple effect determines the disruption-based scope of changes in the system.

2.3 Bullwhip Effect

The *bullwhip effect* is not a new phenomenon in the industrial world (Forrester 1961). The effect can be explained as magnification of variability in orders in the supply chain. In other words, irregular orders in the downstream part of the supply chain become more distinct upstream in the supply chain. This variance can interrupt the smoothness of the supply chain processes as each link in the supply chain will over- or under-estimate product demand, resulting in exaggerated fluctuations (see Fig. 2.8).

Many retailers, each with little variability in their orders, can lead to greater variability for a smaller number of wholesalers, and can lead to even greater variability for a single manufacturer. Main reasons for the bullwhip effect can be divided into behavioural and operational areas (Lee et al. 1997; Sterman 2000):

Behavioural causes

- misuse of base-stock policies
- misperceptions of feedback and time delays
- panic ordering reactions after unmet demand
- perceived risk of other players' bounded rationality.

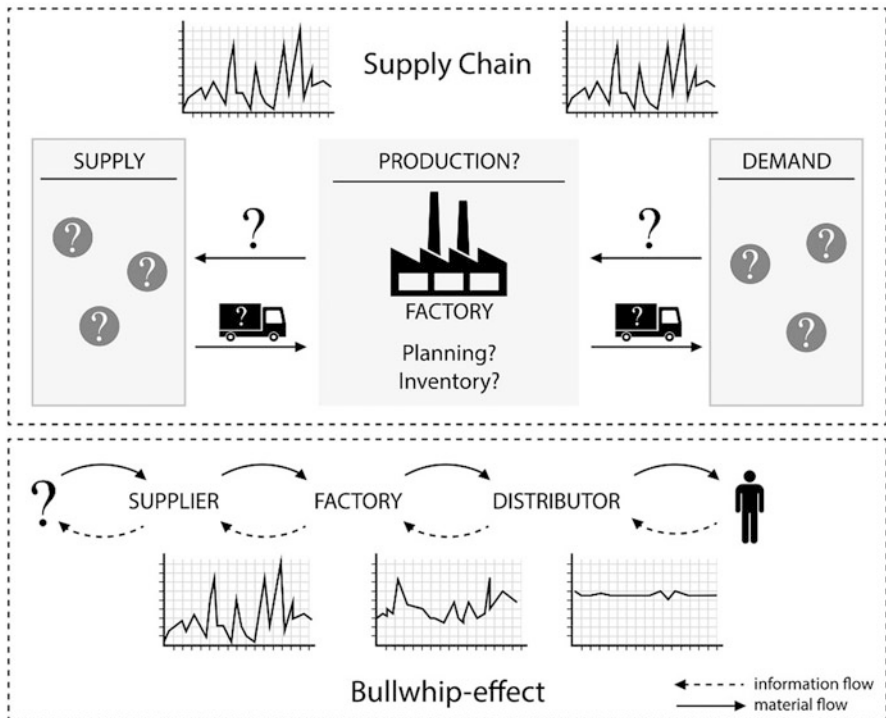


Fig. 2.8 Bullwhip-effect in the supply chain

Table 2.4 Elimination of bullwhip-effect

Reason for bullwhip effect	Countermeasures
Demand non-transparency	Information coordination
Neglecting to order in an attempt to reduce inventory	Automated ordering and monitoring of inventory in order to avoid overstock or shortage
Order batching	Coordinated and accurate lot size definition
Promotions	Use of everyday low prices instead of promotions
Shortage gaming	Validation of customer demand through historical data of customer ordering
Product returns	Policies to control returns or cancelled orders

Operational causes

- dependent demand processing (demand is non-transparent and causes distortions in information in the supply chain)
- lead time variability
- lot-sizing/order synchronization
- quantity discount
- trade promotion and forward buying
- anticipation of shortages.

Negative consequences such as higher safety stocks, inefficient production (surplus or shortage), and low or peak utilization of distribution channels can be recognized. Countermeasures for the bullwhip effect can be identified (Table 2.4).

Consider an example of how demand non-transparency leads to the bullwhip-effect. A fast-moving consumer goods company is facing slight demand variation which leads to huge variation in stocks on the supplier side. The company delivers its product to consumers through the manufacturer and three suppliers. Because of the relatively low cost of changing the production rate compared to the cost of carrying inventory, the company has decided to change its production rate in order to reduce the capital commitment in the form of finished product. The task shows the effect on the manufacturer of a 10% decrease in demand from customers.

For any supplier Eq. (2.1) is used to calculate the production rates:

$$\begin{aligned} \text{New order/production rate} = & \text{Demand new} - \text{Safety stock old} \\ & + \text{Safety stock new} \end{aligned} \quad (2.1)$$

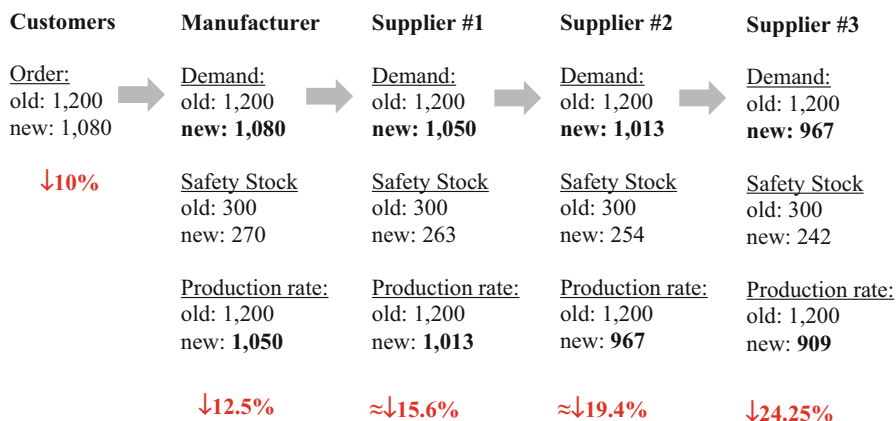
Initial data for analysis is presented in Table 2.5.

Now demand decreases by 10%. Safety stock is 25% of demand and is therefore able to cover demand of 1 week. New demand correlates with the new production rate of the predecessor supply chain member (see Fig. 2.9).

Each player in the supply chain assumes that demand forecast (or orders) for the next period is the same as in the current period. Following this assumption each supplier will be the same as in the current period. Following this assumption each supplier will be planning their production rate to cover the demand/order for the

Table 2.5 Demand data

	Demand old	Order old	Safety stock old
Customer	1200	1200	300
Manufacturer	1200	1200	300
Supplier #1	1200	1200	300
Supplier #2	1200	1200	300
Supplier #3	1200	1200	300

**Fig. 2.9** Implications of the demand fluctuations on production rates (Ivanov et al. 2017a)

next period, which will be equal to the demand/order for the current period (e.g., new demand of supplier #3 orients itself by new production rate of supplier #2). The problem will be that only the manufacturer can see the changes in demand on the customer side. Other players in the supply chain cannot see the changes in demand because of non-transparency. For that reason the players will change their production rate and safety stocks because the predecessor changed his order without pre-informing other supply chain partners.

We can observe that demand non-transparency affects the shortage. For example, Supplier #3 will not produce the right amount of pieces for customers' orders to satisfy their demand.

It can be concluded that changes on the customer side increase order quantity through the supply chain if demand is non-transparent. In general, communication, validation of demand, information sharing, and computer aided ordering and better pricing strategy can help reduce the bullwhip effect in this situation.

2.4 Ripple Effect

2.4.1 Definition

The ripple effect in the supply chain occurs if a disruption cannot be localized and cascades downstream impacting supply chain performance such as sales, stock return, service level, and costs (Ivanov et al. 2014a; Dolgui et al. 2018). The methodical elaborations on the evaluation and understanding of low-frequency-high-impact disruptions are therefore vital for understanding and further development of network-based supply concepts (Tomlin 2006; Liberatore et al. 2012; Sawik 2016).

Details of empirical or quantitative methodologies differ across the works on supply chain disruption management, but most share a basic set of attributes:

- a disruption (or a set of disruptions)
- impact of the disruption on operational and strategic economic performance
- stabilization and recovery policies.

Within this set of attributes, most studies on supply chain disruption consider how changes to some variables are rippling through the rest of the supply chain and impacting performance. We suggest considering this situation, *the ripple effect in the supply chain*, as an analogy to computer science, where the ripple effect determines the disruption-based scope of changes in the system.

Ripple effects are not an infrequent occurrence. In many examples, supply chain disruptions go beyond the disrupted stage; i.e., the original disruption causes disruption propagation in the supply chain, at times still higher consequences are caused (Fig. 2.10).

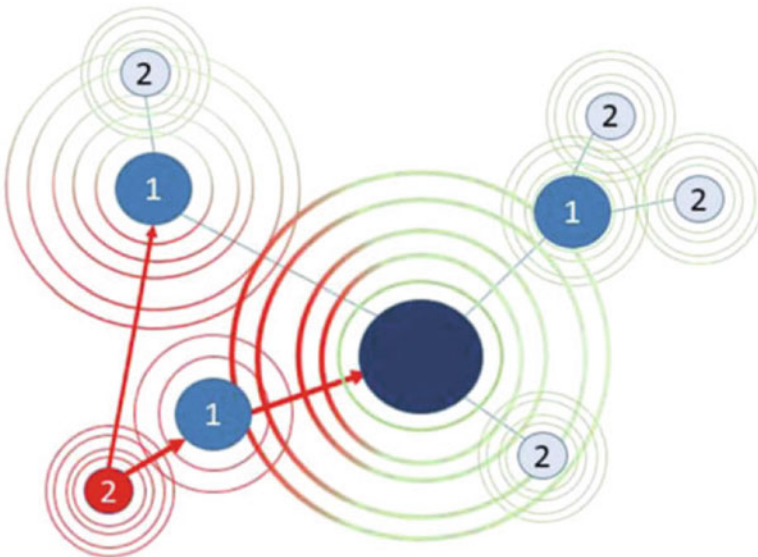


Fig. 2.10 Disruption propagation in the supply chain (Ivanov et al. 2017a)

The ripple effect is a phenomenon of disruption propagations in the supply chain and their impact on output supply chain performance (e.g., sales, on-time delivery, and total profit). It may have more serious consequences than just short-term performance decrease. It can result in market share losses (e.g., Toyota lost its market leader position after tsunami in 2011 and needed to redesign supply chain coordination mechanism). The ripple effect is also known as “domino effect” or “snowball effect”. The reasons for ripple effect are not difficult to find. With increasing supply chain complexity and consequent pressure on speed and efficiency, an ever-increasing number of industries come to be distributed worldwide and concentrated in industrial districts. In addition, globalized supply chains depend heavily on permanent transportation infrastructure availability.

The ripple effect describes disruption propagation in the supply chain, impact of a disruption on supply chain performance and disruption-based scope of changes in supply chain structures and parameters (Ivanov et al. 2014a; Dolgui et al. 2018).

Following a disruption, its effect ripples through the supply chain. The missing capacities or inventory at the disrupted facility may cause missing materials and production decrease at the next stages in the supply chain. Should the supply chain remain in the disruption model longer than some critical period of time (i.e., *time-to-survive* (Simchi-Levi et al. 2015)), critical performance indicators such as sales or stock returns may be affected.

The scope of the rippling and its impact on economic performance depends both on robustness reserves (e.g., redundancies like inventory or capacity buffers) and speed and scale of recovery measures. Therefore, the risks and supply chain resilience should be estimated at the design and planning stages in the proactive mode.

At the control stage in the reactive mode, contingency plans (e.g., alternative suppliers or shipping routes) must happen quickly to expedite stabilization and recovery in order to ensure continuity of supply and avoid long-term impacts. In implementing such recovery policies, companies need a tool supported by collaboration and supply chain visibility solutions for assessing the disruption impact on the supply chain as well as the effects and costs from redirecting material flows. In supply chain management settings, the ripple effect should also include recovery strategies which may compensate for disruptions and avoid their rippling.

It has been extensively documented in literature that severe disruptions may ripple quickly through global supply chains and cause losses in supply chain performance that can be measured by such key performance indicators as revenues, sales, service level, and total profits (Schmitt and Singh 2012; Simchi-Levi et al. 2015; Snyder et al. 2016). Such risks are new challenges for research and industries that face the *ripple effect* arising from vulnerability, instability, and disruptions in supply chains (Liberatore et al. 2012; Ivanov et al. 2014a, b). As opposite to well-known bullwhip effect that considers high-frequency-low-impact *operational risks*, the ripple effect studies low-frequency-high-impact *disruptive risks* (Fahimnia et al. 2015; Simchi-Levi et al. 2015; Sokolov et al. 2016; Snyder et al. 2016).

2.4.2 Reasons for Ripple Effect

Table 2.6 and Fig. 2.11 summarize major reasons and counter-measures for ripple effect.

In the last decade, reasons for disruption in supply chains have been extensively investigated. Hendricks and Singhal (2005) quantified the negative effects of supply chain disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started 1 year before and ended 2 years after a disruption, large negative effects on profitability, a 107% drop in operating income, 7% lower sales growth and an 11% growth in costs, 2 years at a lower performance level after a disruption.

2.4.3 Mitigation Strategies for Ripple Effect

Along with the risk identification, recent literature also discussed the risk mitigation strategies. These strategies can be classified into flexibility and robustness areas with regards to proactive and reactive control stages (He and Zhuang 2016).

Table 2.6 Reasons of the ripple effect and counter-measures

Reasons	Counter-measures
Complexity	Simplification of supply chain structures Structures with necessary conditions of observability and controllability
Leanness	Inventory and capacity buffers Postponement Supply chain design extension
Geographical specialization	Multiple sourcing Contingency plans
IT-failures	Decentralization Cloud services

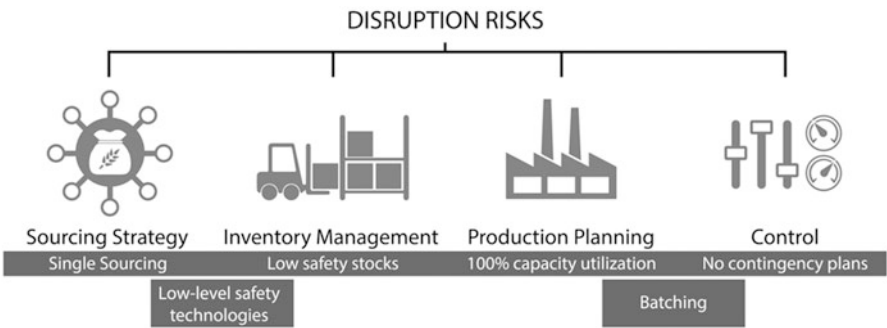


Fig. 2.11 Reasons for ripple effect

Literature has dealt extensively with methods to strengthen supply chains to mitigate uncertainty impacts.

First, different *reserves* (material inventory, capacities) can be referred to. Tomlin (2006) and Chopra and Sodhi (2004) analysed the issues of *risk mitigation inventory* and reserve capacity on supply chain resilience. It should be noted that risk mitigation inventory differs from classical safety stock and is considered to decouple from disruptive risks. For this issue, valuable approaches and models for supply chain design and planning under uncertainty were elaborated.

Second, new *strategies* such as *leagile*, *agile* and *responsive* supply chains can be applied to make supply chains more flexible in a wider sense of the word. The third method is related to better *coordination* in supply chains and refers to the concepts like collaborative planning, forecasting and replenishment. Fourth, a set of *post-poned decisions* (product postponement, rolling/adaptive planning) can be used. All these approaches can be referred to as supply chain *excessiveness*.

The above-mentioned redundancies generally serve for two problem areas. First, they are intended to protect the supply chain against perturbation impacts based on certain reserves. This issue is related to the supply chain *robustness* (Rosenhead et al. 1972). Second, redundancies are created to amplify the fork variety of supply chain paths to react quickly and flexibly to changes of a real execution environment. This issue is related to supply chain *flexibility*.

The *robustness* of supply chains is a complex characteristic of a non-failure operation, durability, recoverability, and the maintaining of supply chain processes and a supply chain as a whole. This is connected with the creation of a reserves system (the introduction of resource excessiveness) for the prevention of failures and deviations in supply chain processes (Meepetchdee and Shah 2007; Ivanov and Sokolov 2013).

Recent literature has identified different methods to strengthen supply chains to mitigate uncertainty impacts and ensure supply chain robustness. Different robustness reserves can include material inventory, capacities buffers, etc. For this issue, valuable approaches and models for supply chain design and planning under uncertainty were elaborated.

The flexibility of supply chains is a property concerning its ability to change itself quickly, structurally and functionally depending on the current execution state and reaching supply chain management goals by a change in supply chain structures and behaviour. This is connected with the creation of an *adaptation system* (with regard to operations and resources) for the prevention, improvement, or acquisition of new characteristics for the achievement of goals under the current environmental conditions varying in time (see also Chap. 3 for supply chain resilience).

Elements of the flexibility and robustness are interconnected (see Fig. 2.12).

Many authors, e.g., Jang (2006), Ozbayrak et al. (2006) and Tang and Tomlin (2008) consider flexibility as a solution for avoiding most of the common business disruptions on the basis of timely and responsive reaction to changes in the supply chain environment. Tachizawa and Thomsen (2007) empirically investigated the aspects of flexibility related to the upstream supply chain. Coronado and Lyons

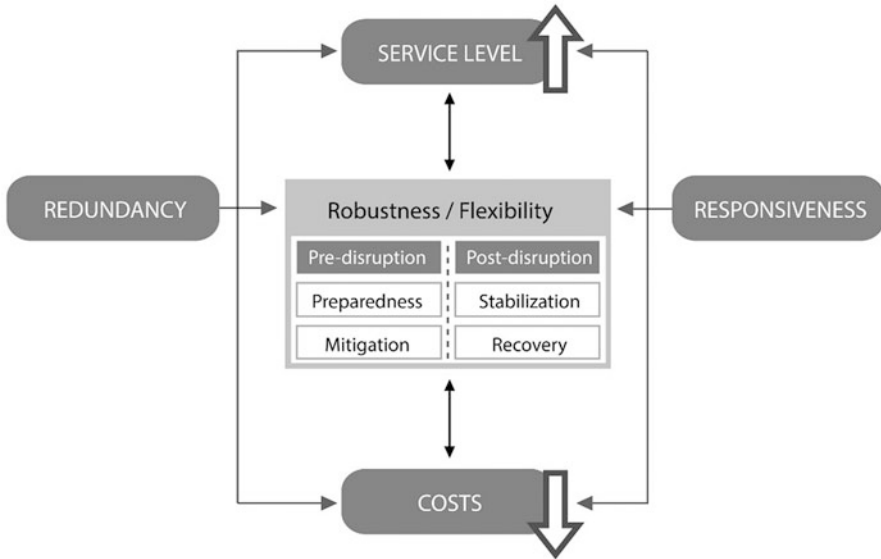


Fig. 2.12 Robustness, flexibility, and performance

(2007) investigated the implications of operations flexibility in industrial supply chains and the effect it had on supporting initiatives designed for build-to-order manufacturing. Wadhwa et al. (2008) presented a study on the role of different flexibility options (i.e. no flexibility, partial flexibility and full flexibility) in a dynamic supply chain model based on key parameters and performance measures.

Swafford et al. (2008) showed that information technology integration enables an organization to tap into its supply chain flexibility, which in turn results in faster supply chain response and ultimately higher competitive business performance. Kauder and Meyr (2009) provided a mathematical optimization framework for a mutual analysis of flexibility and efficiency of supply chain design for an automotive manufacturer. Tanrisever et al. (2012) proposed a stochastic programming model for a multi-stage supply chain regarding capacity flexibility in made-to-order production environments.

Stevenson and Spring (2007) distinguished robust network flexibility as the range of events with which the existing supply chain structure is able to cope, and the reconfiguration of flexibility regarding modification (adaptability) of supply chains. Yadav et al. (2011) analysed the flexibility of supply chain in the context of robustness regarding flexible product families and diversification. Seifert and Langenberg (2011) also considered supply chain flexibility and adaptability with product decisions.

Other aspects of flexibility are coordination and postponement. Coordination has become a key factor in mitigating the *bullwhip effect* and in overcoming information asymmetry (Datta and Christopher 2011; Ouyang and Li 2010). Moreover, it has become possible to integrate customers into supply chain considerations,

resulting in the development of the build-to-order supply chain management (Gunasekaran et al. 2008). Finally, a set of postponed decisions (product postponement or rolling/adaptive planning) can be used (Olhager 2003) to increase supply chain flexibility.

Santoso et al. (2005) provided evidence of the importance of designing robust supply chains and mitigating information asymmetry with the help of coordination throughout. Datta and Christopher (2011) investigated the effects of information sharing and coordination mechanisms for managing uncertainty in supply chains. In addition, adaptive (rolling) planning is frequently applied to mitigate uncertainty by postponing some planning decisions for specific time intervals.

In relating supply chain flexibility to performance, different metrics such as production, capacity, volume, and logistics flexibility have been introduced (Shepherd and Günter 2006). Beamon (1999) and Naim et al. (2006) considered quantity, supply, product, transport, and innovation flexibility. Beamon (1999), Cai et al. (2009), Shepherd and Günter (2006), Stevenson and Spring (2007) emphasized that existing performance measures for supply chain flexibility are not well matched with each other and are, in some cases, contradictory or excessive.

Knoppen and Christiaanse (2007) showed that flexibility in the supply chain (unlike in manufacturing systems) is primarily interrelated with adaptation through managerial actions. Therefore, in supply chains, coordination plays an important role in flexibility and distinguishes this issue from classic automatic control theory. Simchi-Levi and Wei (2015) developed a method for worst-case analysis of process flexibility designs. Basic areas of flexibility include system, process and product flexibility (Fig. 2.13).

System flexibility is composed of structural and strategy components. Companies implement product and process flexibility extensively (see e.g., new Volkswagen production system (VPS) strategy). Coordination and sourcing strategies in supply chains are also typical in practice. Many companies invest in structural redundancy (e.g., Toyota extends its supply chain subject to multiple-

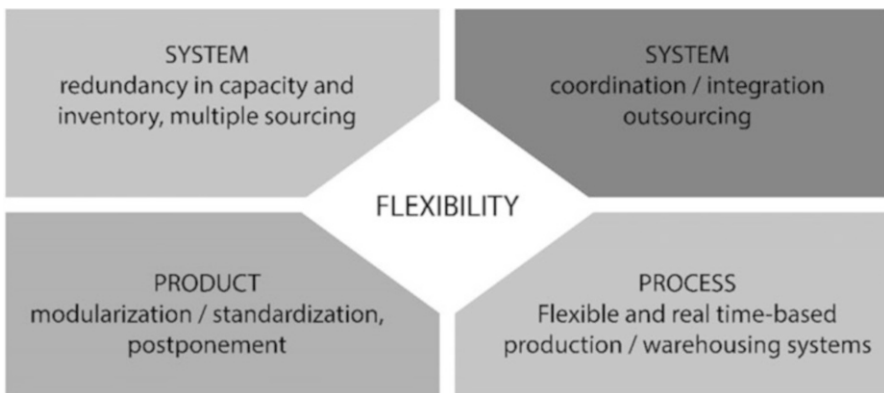


Fig. 2.13 Supply chain flexibility (Ivanov et al. 2014a)

sourcing and building new facilities on the supply side). All these four elements of flexibility can be seen as strategies for mitigating the ripple effect at the mitigation stage and reacting at the post-disruption stage.

2.4.4 Information Technologies for Tackling the Ripple Effect

At the *proactive* level, APS (Advanced Planning and Scheduling) and early warning systems are used at the preparedness stage (Stadtler et al. 2015; Li et al. 2010). Despite the great advantages of recently developed supply chain optimization approaches, the models as currently implemented in APS and supply chain management information systems still do not consider important practical operability objectives such as robustness, stability, flexibility, etc. This situation creates a gap between theory and practice.

Decision-making at the *reactive* level in the case of deviations and structural dynamics is one of the main challenges in supply chain execution (Krajewski et al. 2005; Chandra and Grabis 2009; Ivanov et al. 2010; Vahdani et al. 2011; Bode et al. 2011; Peng et al. 2011). It is concerned with supply chain *control and adaptation* in different uncertainty environments where response and recovery are needed to figure out how best to allocate scarce resources to rebuilding/reconnecting supply chains to ensure process continuity and viability.

Disruptions are hardly predictable, and hence difficult to plan in advance (Kleindorfer and Saad 2005). Supply chain managers spend about 40–60% of their working time recovering from disruptions (Mulani and Lee 2002). Therefore, the supply chain control function becomes more and more important in practice. Feedback control can be supported by RFID (radio-frequency identification) technology which can be used to effectively communicate these disruptions to the other tiers, and help revise initial schedules.

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Chapter 3

Supply Chain Resilience: Modelling, Management, and Control

Supply chain resilience is a multi-facet property that comprises a number of components in both internal supply chain processes and in interaction with the environment (Pettit et al. 2010; Fahimnia et al. 2015; Gupta et al. 2016) (Fig. 3.1).

One of the main objectives of supply chain management is to increase total system output performance, which is basically referred to as supply chain effectiveness (i.e., sales and service level) and efficiency (costs). The achievement of the output performance is the basic imperative for supply chain design, planning and scheduling. At the same time, achievement of planned performance can involve the impact of perturbations in a real-time execution environment. Supply chain execution is subject to uncertainty at the planning stage and disruption at the execution stage. Cost efficiency comes with a huge hidden expense should a major disruption (i.e., a more severe impact than a routine disturbance) occur. This requires supply chain protection against and efficient reaction to disturbances and disruptions. Therefore, supply chains need to be planned to be *stable, robust and resilient* enough to (1) maintain their basic properties and ensure execution; and (2) be able to adapt their behavior in the case of disturbances in order to achieve planned performance using recovery actions.

In recent years, supply chain *resilience* has emerged as an interesting research field and has been extensively studied via different approaches. The general problem focuses on designing a supply chain that is able to achieve the planned or still acceptable performance and to reject a class of disturbances in the presence of severe disruptions (Craighead et al. 2007; Ambulkar et al. 2015; Kamalahmadi and Mellat-Parast 2016; Quang and Hara 2017; Scheibe and Blackhurst 2017; Ivanov et al. 2017; Azadegan and Jayaram 2017). Resilient supply chain design creates certain protections and takes into account possible perturbations while generating supply chain design (Snyder 2006; Klibi et al. 2010), e.g. with the help of contingency plans or backup planning (e.g., alternative suppliers or shipping routes)

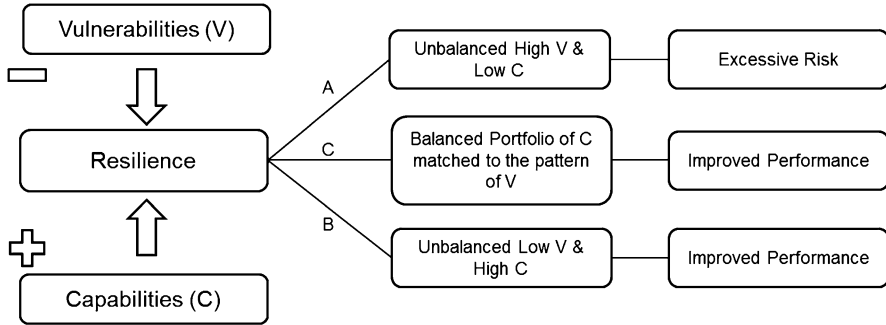


Fig. 3.1 Supply chain resilience concept (Based on Pettit et al. 2010)

(Knemeyer et al. 2009; Cui et al. 2010; Li et al. 2010; Yang et al. 2012; Benyoucef et al. 2013).

The disruption impact on the supply chain performance depends on both proactive resilience measures and recovery contingency plans (Tomlin 2006). Kleindorfer and Saad (2005) and Sheffi and Rice (2005) considered sourcing flexibility, inventory and capacity excessiveness as major resilience drivers in the supply chain. These studies pointed also out that in some cases the planned supply chain performance cannot be restored to the full extent.

In this Chapter, we are especially interested in the following questions:

- What are the objective properties of supply chains regarding uncertainty and performance, and what is the appropriate terminology for their definition?
- What types of problems are typical within supply chain dynamics analysis and control domains?
- How can these properties and problem classes be inter-related and what are the classification features?
- Which of those properties can be quantitatively measured and what techniques or tools can be applied to different types of problems?

The answers to these various questions could be of interest to both academics and practitioners. On one hand, a systematic representation of supply chain dynamics domain taxonomy can be used by researchers, e.g., by identifying problem issues in this domain. On the other hand, improvement of systematic interrelations and application of tools to quantify these interrelations may help to solve many practical managerial problems.

For example, the question of how robustness and flexibility influence supply chain performance both from the cost and benefit points of view, can be investigated in a real-time interrupted execution environment. Another issue is the analysis of the attainability of planned supply chain performance in a real-time execution environment. Finally, supply chain stability and the impact of different adaptation policies on supply chain execution behavior, resilience and performance can be analyzed.

3.1 Terminological Framework: Redundancy, Robustness, Stability, Flexibility, Resilience

In managing supply chain economic *performance* under severe uncertainty, one of the crucial issues is to develop measures for assessing supply chain resistance against the disruptions. Recent literature suggests some indicators to assess the impact of uncertainty on the supply chain execution (cf also Sect. 2.4 of this book). Most popular are robustness, stability, and resilience (Fig. 3.2).

Details of methodologies across the bodies of work on supply chain robustness, stability, and resilience differ. A classification of relevant operability objectives can be found in (Ivanov and Sokolov 2013; Dolgui et al. 2018). Most consider a supply chain that is able to continue execution of planned performance despite disruptions to be *robust* (Klibi et al. 2010; Sawik 2015). The performance of such a supply chain is not effected by the negative impacts of disruptions. A supply chain that is able to continue execution without any changes in plans and achieve the planned performance is called *stable* (Daganzo 2004).

The understanding of stability and robustness depends on the system considered as well as on methods and goals of systems analysis (Meepetchdee and Shah 2007; Ivanov and Sokolov 2013). Stability reflects the current *state* of the system

	System disturbance	System state after disruption	System performance	Costs
Stability			Stable performance (small output variation in regard to a small perturbation)	BIBO (bounded-in-bounded-out) analysis, no additional costs incurred
			Unstable performance (large output variation in regard to a small perturbation)	
Robustness			Non-disrupted performance due to redundancy	Proactive redundancy costs
			Disrupted performance (low redundancy)	
Resilience			Non-disrupted performance due to flexibility	Proactive redundancy costs + Flexibility recovery costs
			Low robustness and flexibility	

Fig. 3.2 Stability, robustness, resilience

(i.e., inventory stability), but does not take into account system *output performance*. The introduction of performance into disturbance analysis typically raises the question of robustness, i.e., guaranteeing reasonable current performance (regarding the current state) and output performance (regarding the final results) over a wide range of uncertainty (Mayne et al. 2000).

With a robustness or reliability analysis, integration of *non-stationary operability performance objectives* into supply chain synthesis (planning) decisions becomes possible. Wu et al. (2007) analysed how disruptions propagated and affected supply networks using disruption analysis network. Wagner and Neshat (2010) proposed a method of quantifying risk using the permanent of an adjacency matrix based on graph theory. Hsu and Li (2011) developed a method to evaluate reliability of the supply chain performance under the demand fluctuations. Sokolov et al. (2016) quantified ripple effect in the supply chain with the help of selected indicators from graph theory.

Some studies incorporated robustness and reliability into the constraints of the mathematical programming models. Peng et al. (2011) introduced p-robustness criterion to ensure the supply chain performs well under normal and disrupted structure. Nair and Vidal (2010) analyzed the correlation between disruption and structural features of network. Li et al. (2013) calculated the rate-of-return on fortification investment to help the decision maker choose either to invest in the fortification or not. Schoenlein et al. (2013) defined robustness as the ability of a multiclass queuing network to remain stable, if the expected values of the inter-arrival and service time distributions are subject to uncertain shifts. However, the dynamic characteristics of the supply chain execution over time and the consequences of disruption and recovery duration still remained under-explored.

The study by Lin et al. (2014) concentrated on the reliability assessment for a multi-state supply chain with multiple suppliers as the probability to satisfy market demand within budget and production capacity limitations. They developed an algorithm in terms of minimal paths to evaluate the network reliability along with a numerical example regarding auto glass. Simchi-Levi et al. (2015) reported on the supply chain risk exposure index that is based on a comparison of time-to-recover and time-to-survive. If the time-to-recover is less than the time-to-survive, the supply chain is considered to be robust. Time-to-recover is considered to be known before optimization.

Simchi-Levi and Wei (2015) developed a method for worst-case analysis of process flexibility designs. Han and Shin (2016) assessed supply chain structural robustness considering disruption propagation in a connected graph. They performed a quantitative assessment of the structural robustness on random networks and compared it with the probability of network disruption due to the random risk. Lin et al. (2017) considered a single commodity multi-state intermodal logistics network with transit stations and routes with three parameters, i.e., route capacity, delivery time and time window. The authors evaluated the system reliability as the probability that the network can successfully deliver sufficient amount of the commodity to meet market demand via several transit stations with consideration of the delivery time threshold and time windows.

The ability to maintain, execute and recover (adapt) planned execution along with achievement of the planned (or adapted, but yet still acceptable) performance is therefore the next objective property of the supply chain. This property is related by most authors to supply chain *resilience* (Ambulkar et al. 2015). Ivanov and Sokolov (2013) described supply chain stability, robustness, and resilience as an integrated control framework. Wang and Ip (2009) and Soni et al. (2014) developed resilience metrics with the use of complex graph theory. Zobel and Khansa (2014) quantified resilience for multiple disruptive events. Xu et al. (2014) developed a quantitative model for analysis of predicted supply chain resilience based on structural evolution against random supply disruptions. Kim et al. (2015) apply graph theory to analyzed the impact of supply chain structure on resilience. This study revealed that the network structure significantly determines the likelihood of disruption.

It is to observe that the terms stability, reliability and robustness are typically used in technical studies. In management studies, redundancy, flexibility and resilience are mostly considered. Our understanding of resilience is that it is based on redundancy that ensures both robustness and flexibility. In this setting, *flexibility* is a system's ability to adapt to situational process and structural changes as an adjustment reaction to internal and external disturbances.

In Fig. 3.3, we summarize relations of redundancy, robustness, resilience and flexibility (see also Chap. 2 and Ivanov and Sokolov 2013).

Robustness is meant as more or less direct usage of redundancy (e.g., using redundant inventory to cope with production capacity disruptions). Flexibility considers indirect usage of redundancy in terms of changing system behavior with the help of re-allocating inventories, capacities, and sourcing facilities in supply chains.

Let us analyze the costs issues. Increase in inventory, additional production capacities, and alternative transportation methods or back-up facilities would increase costs. At the same time, these so-called redundant elements would potentially lead to an increase in sales and service level. The robustness elements would also reduce risk of perturbations which may influence schedule execution. Therefore, target objectives (e.g., on-time delivery) can be better achieved. This will positively influence sales and service level. Redundancy elements may also increase supply chain flexibility and have positive effects on both service level and costs. The resilient state of a supply chain requires a balanced robustness and flexibility which allows for achieving maximum service level with disruption risk considerations at acceptable redundancy costs. These ideas are simplified in Figs. 3.4 and 3.5.

In Fig. 3.4a, a supply chain of a retailer, a warehouse, and a factory is presented. The factory orders 100 units of a product every day from factory that is aligned with the daily production capacity of 100 units. No batching is considered in this simple example. Daily shipments are assumed. The warehouse holds risk mitigation inventory of 700 units as a proactive resilience policy. In Fig. 3.4b, factory capacity is disrupted for 7 days. Considering the risk mitigation inventory of 700 units and daily demand of 100 units, this disruption does not affect supply chain performance

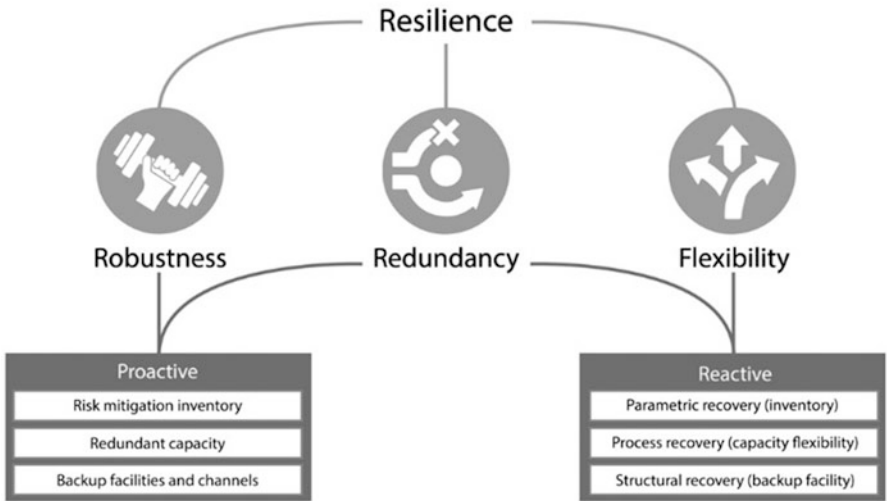


Fig. 3.3 Resilience control elements

in terms of service level, i.e., the ratio of on-time delivered orders to all placed orders.

Now let us consider Fig. 3.5. In Fig. 3.5a, a general framework of supply chain performance and recovery analysis is depicted. The major idea here is to observe the impact of different recovery policies on supply chain performance. Figure 3.5b depicts that in case a factory stops producing for 14 days, service levels will be disrupted since risk mitigation inventory would help for 1 week only. In Fig. 3.5c, it can be observed that usage of back-up factory mitigates the ripple effect and performance decrease. However, both risk mitigation inventory and a back-up capacity increase supply chain costs.

It is evident that through the adaptation, supply chain flexibility and robustness are interrelated. From the dynamics point of view, the robustness elements can also be considered as flexibility elements and the flexibility elements can also be considered as robustness drivers. This is quite natural since both robustness and flexibility serve as “uncertainty cushions” of a supply chain. Balancing the elements of flexibility and robustness at proactive and reactive control loops, different constellations of service level, costs and stability can be analyzed methodically and well-founded and with regard to a risk covering strategy and supply chain management strategy (Fig. 3.6).

Figure 3.6 depicts an example of a typical multi-objective analysis with regards to different proactive and reactive policies. We are interested in investigating the impacts of different combinations of disruptions (i.e., two scenarios in Fig. 3.6), proactive mitigation strategies and reactive recovery policies (A, B, C, and D) on the supply chain performance in form of service level and costs. The combinations

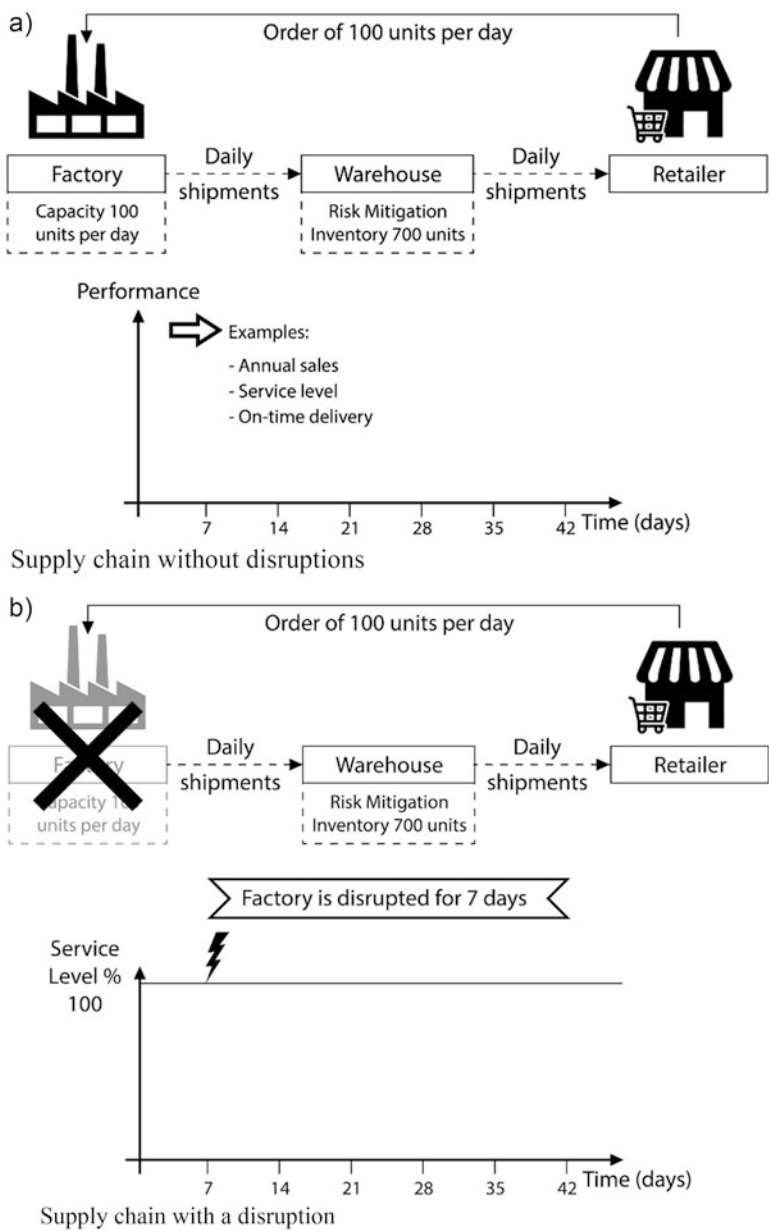


Fig. 3.4 Supply chain with a proactive policy (risk mitigation inventory). (a) Supply chain without disruptions. (b) Supply chain with a disruption

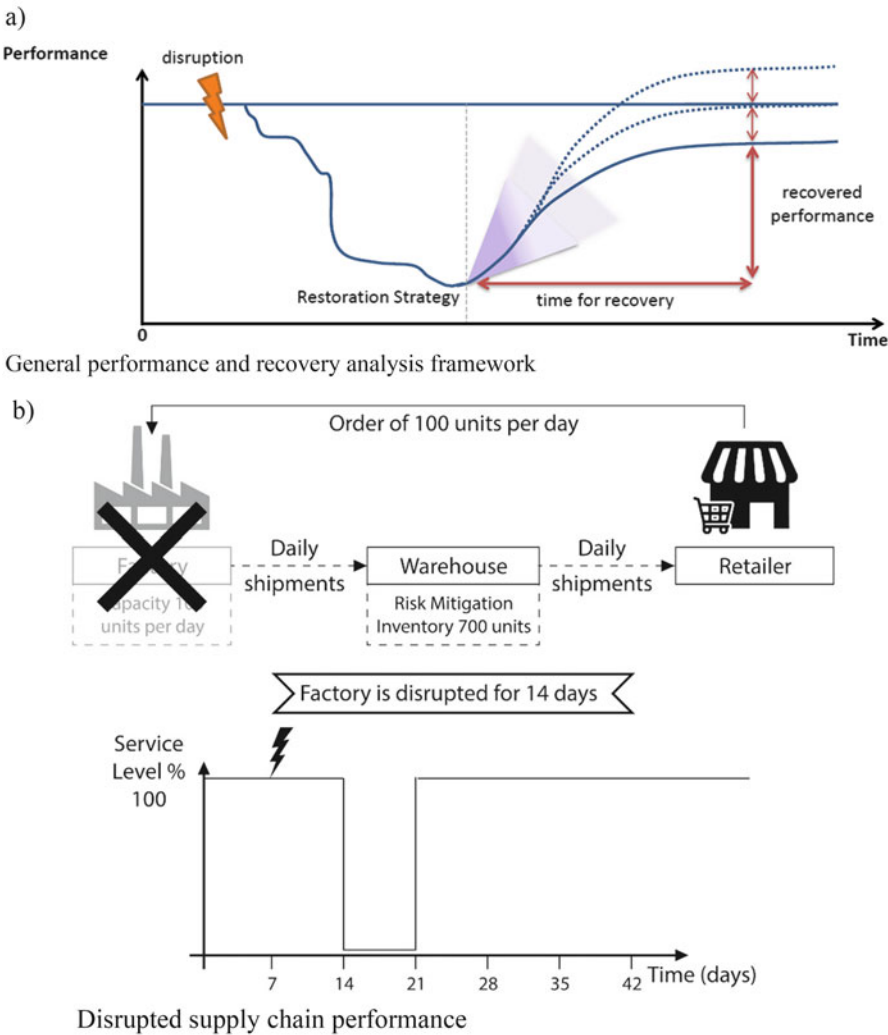


Fig. 3.5 Supply chain with a proactive policy (back-up facility). (a) General performance and recovery analysis framework. (b) Disrupted supply chain performance. (c) Back-up facility as a reactive flexibility strategy

of proactive mitigation strategies and reactive recovery policies (e.g., A – higher risk mitigation inventory, B – a back-up facility, etc.) may differ in costs and service level impacts for different disruption scenarios. The task of quantitative analysis methods is to decide on what proactive and reactive policies need to be selected. In further chapters of this book, we will consider recent literature advancements and describe our own developments in this research field.

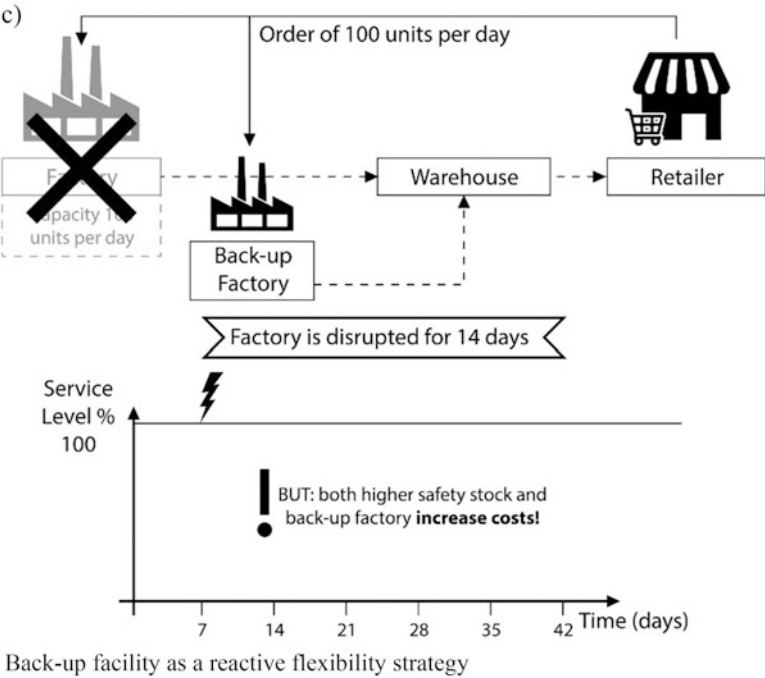


Fig. 3.5 (continued)

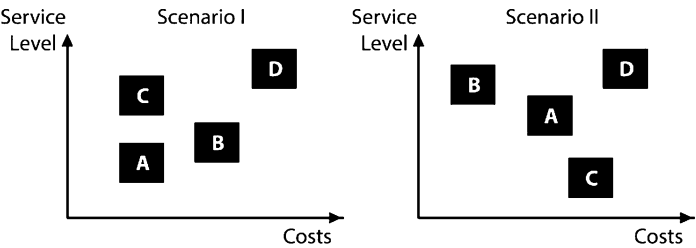


Fig. 3.6 Efficiency vs effectiveness trade-off in supply chain resilience management

3.2 Frameworks for Supply Chain and Operations Disruption Management

In this section, we analyze existing frameworks for supply chain dynamics, control, and disruption management. *Supply chain risk management* is the first paradigm that becomes more and more important. Supply chain disruptions may mean losses of revenue and incur high recovery costs for companies (Sheffi and Rice 2005; Tang and Musa 2011; Ho et al. 2015). Therefore, supply chain risk management can be

considered as a critical capability which helps to identify the potential sources of risk and implement appropriate actions to avoid or contain supply chain vulnerability (Sodhi et al. 2012). A typical supply chain risk management comprises four risk components: identification, assessment, response, monitoring and evaluation.

The supply chain event management framework has been increasingly introduced in practice in the last decade (Ivanov et al. 2013). Supply Chain EM aims at a timely identification of deviations or danger of deviations in supply chains, analysis of deviations and alerts about what disruptions have occurred or may occur, and elaborating control actions to recover supply chain operability.

Supply chain event management is composed of *five main functions*:

- monitoring of processes
- notification of an impermissible parameter deviation
- simulating possible adjustment actions
- selecting a control action to eliminate the deviation
- measuring based upon performance indicators.

Supply chain event management is based on three main drivers. First, the tracking and tracing systems, RFID (radio frequency identification), and mobile devices which are used to provide current information about a process execution. Second, the method of management by exception is used to filter information and to compare actual parameter values with planned ones. Third, the method of event-oriented planning is used to reveal sensitive adjustment actions in the case of negative events.

Events are a critical point in the supply chain event management concept. Events can be negative (“a track has a one-hour delay”); or positive (“a shipment launch is still possible today”). A basis for the alerts and disruption recovery is a tolerance area of execution parameters’ admissible deviations. In supply chain event management, a certain tolerance area of admissible parameters’ deviations is set up to relate events, alerts, and adjustment launching.

If parameter values are outside of this area’s borders, alerts take place. However, two important questions still remain open: (i) how to determine the borders of the tolerance area; (ii) what adjustments should be made to overcome a particular disruption. In the literature, we were unable to find any formalized approach to determine the tolerance area. In practice, these decisions are made on the basis of weakly founded heuristics or just expert analysis.

Altay and Green (2006) proposed a framework for analysis of *OR/MS research in disaster management*. This framework distinguishes the following stages:

- Mitigating
- Preparedness
- Response, and
- Recovery

The mitigation stage considers processes to reduce the risk of deviations already at the planning stage. The preparedness stage includes processes of monitoring and risk control. The response stage is devoted to processes of how to react in the case

of disturbance (i.e., the “first response” solution). The recovery stage includes processes for adaptation (i.e., it must decide on re-planning, correction, or continuation of the planned execution). This classification can be used for structuring existing research on quantitative methods and IT.

A recovery from an unexpected event is frequently illustrated in literature through functions that describe different scenarios. Sheffi and Rice (2005) identified eight typical stages of disruption: preparation; disruption event; first response; initial impact; full impact; preparation for recovery; recovery; and long-term impact. Among these stages, recovery is the longest and most important stage.

Numerous other frameworks for supply chain resilience and disruption management have been proposed by different authors in recent years. For example, empirical framework of global supply resiliency is proposed by Blackhurst et al. (2011) based on recently published study on the severity of supply chain disruptions (Craighead et al. 2007). Pettit et al. (2010) developed a framework where three possible supply chain states are distinguished: excessive vulnerabilities relative to capabilities will result in excessive risk (state A), excessive capabilities relative to vulnerabilities will erode profitability (state B), and supply chain performance improves when capabilities and vulnerabilities are more balanced (state C). A good overview of such frameworks can be found in Zsidisin and Ritchie (2009) and Kouvelis et al. (2012).

3.3 State Dynamics Control

Consider the general concept of state dynamics and supply chain structure reconfiguration (Fig. 3.7):

The dynamic supply chain states can be classified as:

- planned control states $S^{(u)} = \{S_{\alpha}^{(u)}\}$, $\alpha = 1, \dots, N^{(u)}$.
- partially disrupted states with β -level of capability and γ -level of degradation; $S^{(p)} = \{S_{\beta\gamma}^{(p)}\}$, $\beta = 1, \dots, N_1^{(p)}$, $\gamma = 1, \dots, N_2^{(p)}$.
- Disrupted states subject to δ -disruption with η -level of performance degradation: $S^{(o)} = \{S_{\delta\eta}^{(o)}\}$, $\delta = 1, \dots, N_1^{(o)}$, $\eta = 1, \dots, N_2^{(o)}$.

In Fig. 3.7, S_L is the state where all supply chain elements are disrupted and degradation level is maximal. The state transitions can be classified into:

- D-transitions caused by supply chain element disruptions leading to capability decrease and/or performance decline,
- H-transitions caused by reaching minimal parameter values for maintaining supply chain stability/robustness, e.g., minimal inventory levels,
- B-transitions caused by supply chain recovery (on the structural level, e.g., production factory recovery after a fire)

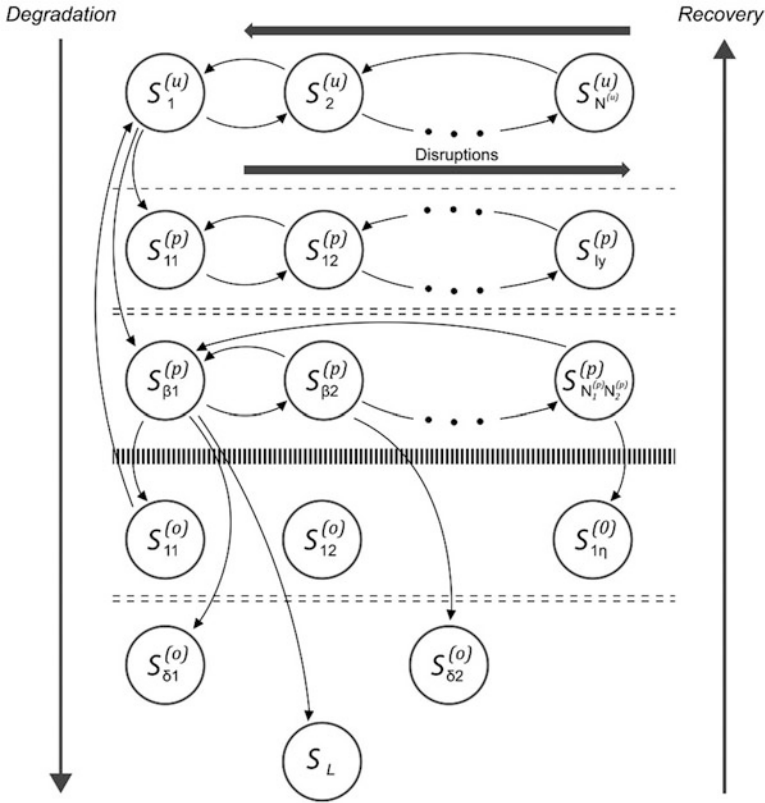


Fig. 3.7 Degradation and recovery dynamics

- K-transitions caused by supply chain stabilization actions (on the parametrical level, e.g., inventory replenishment)

In Fig. 3.7, D-transitions follow the degradation arrow, H-transitions follow the disruption arrow, B-transitions follow the recovery arrow, and K-transitions follow the stabilization arrow.

3.4 Control-Theoretic Supply Chain Resilience Framework

Control theory has been recognized in literature as a sound methodology to model supply chain resilience (Spiegler et al. 2012; Ivanov and Sokolov 2013). Consider the following notations in line with studies (Ivanov and Sokolov 2013 and Ivanov et al. 2014):

- supply chain execution plan (e.g. an inventory policy or a schedule); we define it generally as the control vector $\mathbf{u}_{pl}(t)$ within the area of allowable control inputs $U(\mathbf{x}(t), t)$,
- supply chain redundancy (e.g. excessive inventory, alternative suppliers, etc.); we define redundancy parameters as the vector $\boldsymbol{\alpha}(t)$,
- perturbation impact (e.g., fire at a warehouse); we define it generally as the perturbation vector $\boldsymbol{\xi}(t)$ within the area of perturbations $\Xi(\mathbf{x}(t), t)$
- current state (i.e., inventory level); we define it generally as the state vector $\mathbf{x}(t)$,
- disturbance (i.e., change in the supply chain planned execution); we define it as the disturbance vector $\mathbf{z}(t)$,
- adaptation (i.e., the active control actions to change planned supply chain behavior); we define the adjustable control actions vector as $\mathbf{v}(\mathbf{x}(t), t)$ within the area of allowable real-time regulation control inputs $\mathbf{V}(\mathbf{x}(t), t)$ and parameters being affected by the disturbance and to be adjusted as the vector $\boldsymbol{\beta}$,
- output performance (e.g., service level, costs, etc.); we define it generally as the planned performance vector $\mathbf{y}(t)$ and current performance vector $\mathbf{y}'(t)$ with performance measures $\mathbf{J}_{\boldsymbol{\theta}}^T$ at the end of the planning horizon,
- disruption (i.e., the change in the supply chain planned execution that cannot be adjusted by an adaptive control action and leads to the re-planning of the output performance); we define it generally as the disruption vector $\mathbf{z}'(t)$.

In terms of the notations mentioned above, the dynamics of state and output vectors for the general case can be described as follows:

$$\dot{\mathbf{x}}(t) = \tilde{\boldsymbol{\Phi}}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\xi}(t), \boldsymbol{\alpha}, \boldsymbol{\beta}, t) \quad (3.1)$$

$$\mathbf{y}(t) = \tilde{\boldsymbol{\Psi}}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\xi}(t), \boldsymbol{\alpha}, \boldsymbol{\beta}, t) \quad (3.2)$$

All the described vectors should meet space–time limitations; in other words, the vectors should belong to given sets (Eqs. 3.3–3.5):

$$\mathbf{u}(t) = \left\| \left\| \mathbf{u}_{pl}^T(t), \mathbf{v}^T(\mathbf{x}(t), t) \right\| \right\|^T; \quad \mathbf{u}_{pl}(t) \in \mathbf{Q}(\mathbf{x}(t), t); \quad \mathbf{v}(t)(\mathbf{x}(t), t) \in \mathbf{V}(\mathbf{x}(t), t), \quad (3.3)$$

$$\boldsymbol{\xi}(t) \in \Xi(\mathbf{x}(t), t); \quad \boldsymbol{\beta} \in \mathbf{B}, \quad (3.4)$$

$$\mathbf{x}(t) \in \mathbf{X}(\boldsymbol{\xi}(t), t), \quad (3.5)$$

where $\mathbf{B}$ is an area of allowable parameter values (e.g., an inventory level) and $\mathbf{X}(\boldsymbol{\xi}(t), t)$ is an area of allowable states.

There are additional constraints for the initial state and the final state:

$$\mathbf{x}(T_0) \in \mathbf{X}_0(\boldsymbol{\beta}), \mathbf{x}(T_f) \in \mathbf{X}_f(\boldsymbol{\beta}). \quad (3.6)$$

Equation (3.6) determines the end conditions for the supply chain state vector $\mathbf{x}(t)$ at time $t = T_0$ and $t = T_f$ (T_0 is the initial time of the planning interval in which the supply chain is being investigated, and T_f is the end time of the planning interval).

Finally, let us introduce the following vector of the *multi-model quality functional* (total performance metric) to evaluate supply chain performance at the end of the operation period:

$$\mathbf{J}_\theta(\mathbf{x}(t), \mathbf{u}(t), \xi(t), \boldsymbol{\beta}, t) = \|\mathbf{J}\|^T. \quad (3.7)$$

Four basic execution control scenarios (corresponding to arrows outgoing from the F-block) are possible:

- a perturbation does not affect the supply chain execution, supply chain continues execution according to the planned execution policy $\mathbf{x} = \mathbf{f}(t, \mathbf{x}, \mathbf{u})$,
- a perturbation does not affect the supply chain execution since the planned robustness $\boldsymbol{\alpha}(t)$ allows continued execution according to the planned state $\mathbf{x} = \mathbf{f}(t, \mathbf{x}, \mathbf{u})$,
- a perturbation affects the supply chain execution subject to β -parameters, then components of $\mathbf{J}_\theta^T$ deviate from the plan, but then $\mathbf{x} = \mathbf{f}(t, \mathbf{x}, \mathbf{u})$ can be recovered with the help of a correcting program $\mathbf{v}(t)$ through the construction of $\mathbf{x}_\sigma = \mathbf{f}(t, \mathbf{x}, \mathbf{v})$, and the desired output performance can be achieved,
- a perturbation affects the supply chain execution subject to β -parameters, and then components of $\mathbf{J}_\theta^T$ deviate from the plan. No correcting program $\mathbf{v}(t)$ can be found to offer an updated $\mathbf{x}_\sigma = \mathbf{f}(t, \mathbf{x}, \mathbf{v})$ in order to achieve the planned $\mathbf{J}_\theta^T$. In this case, a change in master plan, in supply chain design, or in the planned performance $\mathbf{J}_\theta^T$ or influencing D or S are needed in order to calculate a feasible $\mathbf{u}^*(t)$.

These four control scenarios can be brought into correspondence with some analysis domains for the ripple effect and with the control business processes.

3.4.1 Case 1: Stability

In this case, the ability to cope with volatility and to continue a planned execution without any changes after being perturbed is investigated. This problem case considers current system space and current performance. The main analysis category for this problem case is *stability*, which characterizes continuity of systems' behavior.

For the general case (Eqs. 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, and 3.7), the stability condition can be described through the stability of adaptive systems (partially unknown systems) as follows:

$$\|\mathbf{y}'(t) - \mathbf{y}_{pl}(t)\| < \varepsilon, \quad (3.8)$$

where $\mathbf{y}_{pl}$ is a general vector of planned characteristics, ε is given small value.

3.4.2 Case 2: Robustness

The main analysis category for this scenario is *robustness*, which characterizes the ability to perform planned execution under disturbances (Mayne et al. 2000). Robustness is a complex characteristic of the supply chain operation, durability, and the maintenance of planned parameters with the help of certain redundancies in a supply chain (e.g., safety stocks).

The main elements of the *robustness reserves* are time buffers, safety stocks, and additional facilities and reservations of capacities. These elements involve certain *costs* for the creation of reliability reserves, their maintenance, and recovery handling in the case of disruption, and application of these reserves to recover the supply chain processes, multi-variate and modular production. However, in the case of perturbation, these reserves may also be of *profit* origin because of uninterrupted supply chain processes.

3.4.3 Case 3: Resilience

In this case, the ability to maintain, execute, and recover (adapt) the planned execution along with achievement of the planned (or adapted, but yet still acceptable) performance is investigated. This problem case considers a current system space, both current and output performance as well as active control actions (i.e., the adaptation) to change planned supply chain behavior. The main analysis category for this problem case is *resilience*, which characterizes the *adaptation-based* achievement of planned supply chain performance in conditions of disturbances of differing severity.

Let us extend the general case (3.1), (3.2), (3.3), (3.4), (3.5), (3.6), (3.7), and (3.8) by introducing adjustable control actions vector $\mathbf{v}(\mathbf{x}(t), t)$. Then, it is necessary to obtain $\mathbf{u}_p(t)$, $\mathbf{v}(\mathbf{x}(t), t)$, $\boldsymbol{\beta}$ such that the generalized functional $J_G = J_G(\mathbf{J}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(\mathbf{x}(t), t), \boldsymbol{\xi}(t)))$ possesses its extreme values. The adjustable control actions vector $\mathbf{v}(\mathbf{x}(t), t)$ can also be embedded in the stability condition.

3.4.4 Case 4: Viability

In this case, viability is the ability to survive and exist after a disruption. This is the most severe case concerned with the re-design of the supply chain structure and re-planning economic performance with long-term impacts. The engineering control framework of supply chain resilience is shown in Fig. 3.8.

The $\mathbf{y}(t)$ is the supply chain output performance measured by a monitoring system F with regards to compliance with the input variables $x_{pi}(t)$ that in, turn are subject to supply chain goals $x(t)$ of a superordinated level (e.g. service level

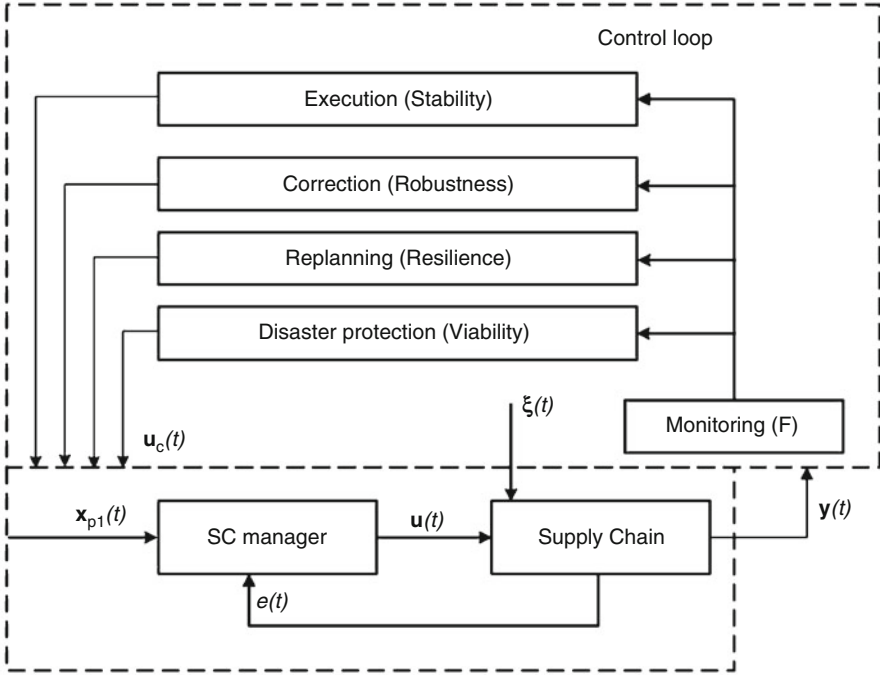


Fig. 3.8 Engineering control framework of supply chain resilience (Based on Ivanov and Sokolov 2010)

and costs). Based on current information from the F negative perturbation influences ξ (e.g. new demand forecasts, disruptions in current processes), $\varepsilon = \|\mathbf{y}'(t) - \mathbf{y}_p(t)\|$ is deviation of output parameters, an adapted input $u_c(t)$ will be given to the controller (C) that is responsible for adjustment control actions $u(t)$ to the system under control P (i.e., the supply chain).

In many practical cases, incremental supply chain planning and scheduling is working without the F -driven feedback system. Such an approach can be justified for such problems as those where a single schedule computation should be fulfilled. These problems may be of either a very strategic nature or a very operative nature. In the most tactical–operational problems that refer to the supply chain dynamics to be under control, the negative feedback concepts as shown in Fig. 3.6 is mandatory.

One of the efficient approaches to implement control of the systems in this class is adaptive planning. Adaptive planning uses not only simple open time slots (in contrast to incremental planning) but employs conflict-driven plan changes during the system execution. Adaptive planning implies problem resolution and redefinition through the learning process, rather than problem solving. This is the *first* strong contribution of control theory to the supply chain management domain. It lets us interpret planning and scheduling not as discrete operations, but as a continuously adaptive process.

The feedback systems are preferably characterized by disturbance elimination, by process execution under uncertainty even if the model structure does not completely correspond to real processes and by the stabilization of unstable processes. The possibility of covering the whole supply chain dynamics and the permanent changes in the supply chain processes and environment without the strong necessity to accomplish total “re-modeling” is ultimately the *second* strong contribution of control theory to supply chain planning and scheduling domain.

Based on the feedback loops, the integration of the planning and scheduling stages is possible. The system output $y(t)$ under control can be expressed either as goals of order realization in the supply chain (i.e. lead time) or as goals at a super-ordinated level (i.e. service level and supply chain costs). Indeed, a supply chain manager is usually more interested in achieving the desired service level and supply chain costs than minimizing the lead time of a number of production orders. Of course, theoretically, a set of interlinking operational (the lead time) and tactical (the service level) goals can be constructed so that the operational goals may be subject to optimization. However, these constellations will be very specific to different concrete supply chains. Hence, we prefer to consider primarily the tactical goals as being subject to optimization and control.

This means that not only is a problem solution in a fixed environment (the system under control) but also a simultaneous consideration of system formation and management problems’ solution in this system are possible. This aspect is of significant practical importance. In practice, the challenge is not to calculate optimal schedules to optimize local order fulfilment parameters but to schedule supply chains subject to the achievement of supply chain goals with regard to profitability and stability.

Modern control theory provides the possibility to model and solve more realistic planning problems (incorporating dynamism and uncertainty) as systems can be modelled in terms of dynamic multi-structural macro-states, based on the simultaneous consideration of management as a function of both states and structures. This approach has been referred to as structure dynamics control theory. Applications of this theory to the supply chain management domain have been presented in Ivanov et al. (2010, 2012, 2014). Also, a wide range of different supply chain properties such as stability, controllability, and observability can be reflected within the control theory.

A supply chain manager plans execution programs subject to “normal” conditions ($\mathbf{u}_p(t)$) and disasters ($\mathbf{u}_d(t)$). Monitoring results (subject to error measurement e) through a supply chain visibility system guides the supply chain manager to one of the control business processes on the basis of an integrated analysis of execution and economic performance. A stabilization plan ($\mathbf{u}_\xi(t)$) and a recovery plan are then developed in collaboration with other parts in the supply chain.

The input data for supply chain adaptation is gathered during the supply chain’s functioning at the state $S_{\delta-1}$ and is received for the state S_δ . Thus we obtain the general formal statement of this problem class

$$J_G = J_G(\mathbf{x}(t), \mathbf{u}_{pl}(t), \mathbf{v}(\mathbf{x}(t), \boldsymbol{\xi}), \boldsymbol{\xi}) \rightarrow \max_{\mathbf{u} \in \Delta}, \quad (3.9)$$

$$\Delta = \mathbf{Q}(\mathbf{x}(t)) \times \mathbf{V}(\mathbf{x}(t), \boldsymbol{\xi}, t), \quad \mathbf{u} = \mathbf{u}_{pl}(t) \times \mathbf{v}(\mathbf{x}(t), \boldsymbol{\xi}) \quad (3.10)$$

We shall distinguish the following types of real-time control in the supply chain:

- *Process correction* or selectable control (dispatching) is a selection of control inputs appropriate for the current situation. It is based on reserves of different types and on the alternating of functioning modes.
- *Plan correction* (control inputs produced as a function of the difference $\Delta \mathbf{x}(t)$ between the planned state trajectory and the real one, under the assumption that $\Delta \mathbf{x}(t) < \varepsilon_1$ (ε_1 is a given value) and that perturbation inputs $\boldsymbol{\xi}(t)$ are stochastic processes with known or evaluated characteristics).
- *Real-time re-planning* is the construction of a new plan and the production of appropriate correcting inputs for the transition from the actual supply chain state trajectory $\mathbf{x}(t)$ to the planned one $\mathbf{x}_{pl}(t)$ at the time interval $(t', t''] \in (T_0, T_f]$ or by the final time: $\mathbf{x}(T_f) = \mathbf{x}_{pl}(T_f)$. A modification of this task is also possible when the difference is minimized:

$$\Delta \mathbf{x}(t) = \int_{t'}^{t''} (\mathbf{x}(\tau) - \mathbf{x}_{pl}(\tau))^T (\mathbf{x}(\tau) - \mathbf{x}_{pl}(\tau)) d\tau, \quad (3.11)$$

$$\Delta \mathbf{x}(T_f) = (\mathbf{x}(T_f) - \mathbf{x}_{pl}(T_f))^T (\mathbf{x}(T_f) - \mathbf{x}_{pl}(T_f)). \quad (3.12)$$

In this setting, we understand under resilience as that the ability to maintain, execute and recover (adapt) the planned execution along with achievement of the planned (or adapted, but yet still acceptable) performance is investigated. This problem case considers current system space, both current and output performance as well as active control actions (i.e., the adaptation) to change planned supply chain behavior. The main analysis category for this problem class is *resilience*, which characterizes the *adaptation-based* achievement of planned supply chain performance in conditions of disturbances of differing severity.

Let us extend the general case (3.1), (3.2), (3.3), (3.4), (3.5), and (3.6) by introducing the adjustable control actions vector $\mathbf{v}(\mathbf{x}(t), t)$ into Eqs. (3.1), (3.2), and (3.6). Then, it is necessary to obtain $\mathbf{u}_{pl}(t)$, $\mathbf{v}(\mathbf{x}(t), t)$, $\boldsymbol{\beta}$ such that the generalized functional $J_G = J_G(\mathbf{J}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(\mathbf{x}(t), t), \boldsymbol{\xi}(t)))$ possesses its extreme values. The adjustable control actions vector $\mathbf{v}(\mathbf{x}(t), t)$ can also be embedded in the stability condition. In this problem class, specific estimation (observation) problems, monitoring problems and problems of supply chain structural state identification exist; for the general case (3.1), (3.2), (3.3), (3.4), (3.5), (3.6), (3.7), and (3.8) it is necessary to obtain structural state estimation $\hat{\mathbf{x}}(t')$ and structure parameters estimations $\hat{\boldsymbol{\beta}}$; here $t', t \in (T_0, T_f)$.

3.5 Supply Chain Resilience Analysis with the Help of Attainable Sets

The *problem* consists of the resilience analysis of different supply chain design structures with regards to different disruption and recovery policies impact on performance subject to J_1 as sales volume and J_2 as profit (Ivanov et al. 2016a, b). The following issues are included in the analysis and captured by the model:

- Achievement (attainability) of planned sales volumes and profits as resilience indicators
- Simultaneous recovery computation and performance impact assessment
- Multiple objective views: logistics (costs minimization), customer (service level), system (sales and supply chain resilience)
- Time duration of a disruption is modelled as continuous time function in dynamic model
- Impact of disruptions on the economic performance which is simulated using a hybrid dynamic optimization model

The idea of a supply chain design resilience index computation comes down to the calculation of performance indicators J_1 and J_2 subject to disruption scenarios defined by a piece-wise function $\xi_{ij}(t)$ by varying its values of in the range $[0;1]$ for a given supply chain execution policy $\mathbf{u}^*(t)$ (e.g., a distribution plan). Let the admissible degradation limits for J_1 and J_2 be as shown in Eq. (3.13):

$$J_1 \leq J_{a1}, J_2 \leq J_{b1}. \quad (3.13)$$

They construct an area P_J in the performance indicator space. The area P_J needs now to be related to all possible outcomes of the execution policy $\mathbf{u}^*(t)$ subject to varying the values of $\xi_{ij}(t)$. Denote $\mathbf{x}_0 = \mathbf{x}(T_0)$ as the initial state vector (i.e., the planned parameters such as delivery quantities, inventory, etc. at the beginning of the planning horizon); $\mathbf{x}_f = \mathbf{x}(T_f)$ is the final state vector (i.e., the same planned parameters but at the end of the planning horizon); $U(\mathbf{x}(T_0))$ is the set of allowable control programs (i.e., supply chain execution policies), $\xi(t)$ is the perturbation vector at the moment t , $\Xi = \{\xi(t) | \xi_1(t) \leq \xi(t) \leq \xi_2(t)\}$ is the set of considered perturbations, where $\xi_1(t), \xi_2(t)$ are prescribed vector functions, which define the minimum and maximum values of the perturbation effects on the realization stage for each fixed supply chain design.

The range of outcomes of execution policies in the presence of disruptions is an attainable set. An attainable set is a fundamental characteristic of any dynamic system. An attainable set in the state space depicts the possible states of a supply chain design subject to variations of the model parameters (e.g., different capacities and processing times). In order to interconnect supply chain execution and the performance analysis to the attainable set in the state space, an attainable set in the performance space has to be constructed. Let us introduce the notation for an attainable set. $\mathbf{D}_x(t, T_0, \mathbf{x}(T_0), U(\mathbf{x}(T_0)))$ is an attainable set in the state space,

$\mathbf{D}_J(t, T_0, \mathbf{x}(T_0), \mathbf{U}(\mathbf{x}(T_0)))$ is an attainable set in the performance indicators' space, and $\tilde{\mathbf{D}}_J^\xi(t, T_0, \mathbf{x}(T_0), \Xi, \mathbf{U}(\mathbf{x}(T_0)))$ is an approximated attainable set under the disturbances at the moment t .

The *justification of the choice* of the attainable set method is related first of all to its dynamic nature (Chernousko 1994; Clarke et al. 1995) and previous attainable set application to supply chain management (Ivanov et al. 2016a, b). An attainable set may be favorable to obtain estimations of performance attainability and to consider perturbations and attainability abilities as *time functions*. The perturbation functions may be set up for different data, including interval perturbations [0;1]. An attainable set allows multi-objective considerations. In most cases, it is possible to approximate attainable set, e.g., to a rectangular form while estimating the outcomes at four points of an attainable set.

The resilience index calculation comes down to computing the intersection area $S_k(\mathbf{u}_l(t))$ of the sets $\overline{\overline{D}}_J^{(\xi)}(T_f, T_0, X_0, \Xi, \mathbf{u}_l)$ and P_J according to condition (3.14)

$$S_k(\mathbf{u}_l(t)) = \min_{1 \leq l \leq L} \max_{1 \leq k \leq K} S_k(\mathbf{u}_l(t)) \quad (3.14)$$

If, for an $\mathbf{u}_l(t)$, ($l = 1, \dots, L$) under perturbations $\xi_j(t)$, the requirement $\overline{\overline{D}}_J^{(\xi)}(T_f, T_0, X_0, \Xi, \mathbf{u}_l) \subset P_J$ is fulfilled, the $S_k(\mathbf{u}_l(t)) = 0$ and the supply chain design is resilient for considered scope and scale of disruptions and recovery policies. The $S_k(\mathbf{u}_l(t)) = 0$ and the supply chain design is resilient for considered scope and scale of disruptions and recovery policies. In other words, feasible J_1 and J_2 deviations are considered to be acceptable for the considered $\mathbf{u}_l(t)$ and $\xi_j(t)$.

If $P_J \cap \overline{\overline{D}}_J^{(\xi)}(T_f, T_0, X_0, \Xi, \mathbf{u}_l) = S_k(\mathbf{u}_l(t)) > 0$, the supply chain resilience decreases. The *larger the intersection area* of the two areas, the less resilient is the supply chain design. Therefore, each of the alternative supply chain designs, performance indicators with different values (as declined by the disruptions) and the corresponding resilience index values for different disruption and recovery scenarios can be calculated. In the ideal case, there should be no intersection and the resilience index is zero, i.e., the considered perturbation impacts and resulting variance of the control variables do not affect the performance. In the following, we provide a technical description to calculate attainable set and resilience index.

An attainable set needs to be found that represents the set of all possible execution scenarios which may occur in the supply chain execution after the disruptions. We propose this area to be named as the attainable set in the state space under disturbances defined as follows:

$$D_x^{(\xi)}(T_f, T_0, X_0, \Xi, \mathbf{u}_l) \quad (3.15)$$

One possible option to construct the attainable set $D(T_f, T_0, \mathbf{x}(T_0))$ is multiple numerical solution of the task (3.16)

$$J''_G(\mathbf{x}(\cdot)) = \mathbf{c}^T \mathbf{x}(T_f) \rightarrow \min_{\mathbf{u} \in \mathcal{Q}(\mathbf{x})}, \quad (3.16)$$

where $\mathbf{c}$ is the normalized vector $\|\mathbf{c}\| = 1$. Having $\mathbf{u}^*(t)$ for each fixed $\mathbf{c}$, we get a point $\mathbf{x}^*(T_f)$ in the attainable set and the hyperplane $\mathbf{c}^T \mathbf{x}^*(T_f)$ to this attainable set $\mathbf{x}^*(T_f)$. Attainable set is calculated from the main OPC vector by varying the perturbation impacts as control variables. Therefore, the attainable set can be calculated for the perturbed supply chain execution policies. In varying these perturbations at each instant of time over the supply chain execution policy within the time interval and setting these variations into the initial differential system, a set of points where the supply chain performance can be steered to is generated (i.e., the attainable set $D_J^{(\xi)}(T_f, T_0, X_0, \Xi, \mathbf{u}_I)$).

As the dimensionality of the attainable set is high, the construction of an attainable set is a rather complicated problem. When we consider real numbers, it is clear how they are represented in the software. For sets, this is the most important topic. It is why intervals, boxes, and ellipsoids are used. For this reason, an attainable set is usually approximated in different forms. We suggest a rectangular approximation of the attainable set based on four points (a supply chain design with the best value of J_1 , a supply chain design with the best value of J_2 , a supply chain design with the worst value of J_1 , and a supply chain design with the worst value of J_2). Then for an attainable set approximation, the task is to solve problem (Eq. 3.17):

$$\begin{aligned} \min\{J'_1 = J_2 | \xi_j(t) \in \Xi\}; \min\{J'_2 = -J_2 | \xi_j(t) \in \Xi\}; \\ \min\{J'_3 = J_1 | \xi_j(t) \in \Xi\}; \min\{J'_4 = -J_1 | \xi_j(t) \in \Xi\} \end{aligned} \quad (3.17)$$

In problem (3.17) we have four sub-problems each with a single criterion. The meaning of problem (3.17) is that from the set of feasible supply chain design for different data scenarios, four points are selected which correspond to the best and worst values for J_1 and J_2 , respectively. The result of solving this problem are the coordinates of the points $\mathbf{J}'_1, \mathbf{J}'_2, \mathbf{J}'_3, \mathbf{J}'_4$, which makes it possible to construct an attainable set approximation. Such an approximation as a rectangular makes it possible to represent the attainable set $\mathbf{D}_J^\xi$ also as a rectangular one similar to P_J . The points within the area of the intersection of the two rectangles $\mathbf{D}_J^\xi$ and P_J include the possible outcomes for non-achievement of planned performance in the presence of perturbations. This area explicitly reflects supply chain resilience and can be easily quantified due to a rectangle resulting from four-point approximation.

In the example in Fig. 3.9, the resilience index was calculated as the area of intersection of two rectangles defined by the attainable set and the limits on its performance.

The first (grey color) rectangle is constructed on the basis of the above-mentioned admissible values of the performance indicators. After running the model (3.1), (3.2), (3.3), (3.4), (3.5), and (3.6) subject to different execution scenarios, different attainable sets (i.e., the blank rectangles) have been generated for supply chain design #1 and #2, respectively. Recall that in an attainable set, a certain range of supply chain process executions and the corresponding variation of

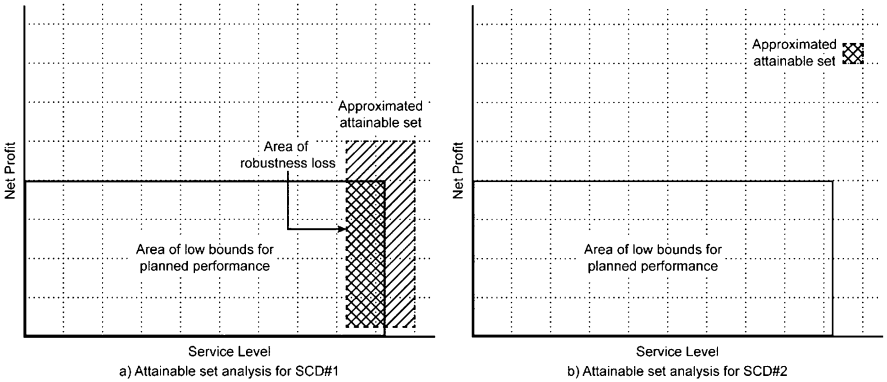


Fig. 3.9 Different resiliencies of the supply chain design structures: (a) a less resilient case, and (b) a more resilient case

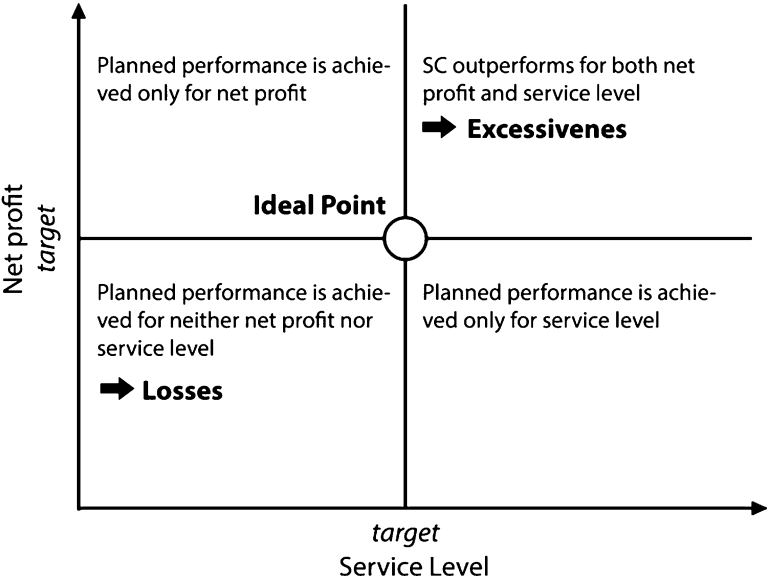


Fig. 3.10 Managerial meaning of the attainable set-based supply chain resilience analysis

the performance indicators are determined. This means that the greater the intersect region of the two rectangles is, the less resilient is the supply chain design. In Fig. 3.10, the managerial meaning of the attainable set-based supply chain resilience analysis is depicted.

If, for example, desired performance is bounded by the values J_1 and J_1 , the attainable set from Fig. 3.9 shows the attainability of the desired performance for all considered execution scenarios and perturbations. For example, in the

excessiveness area, all the points in the attainable set lie outside the rectangle P_j created by the limits on the minimal desired performance. This may be an indication of excessive resilience reserves (e.g., excessive inventory and capacity buffers). In this case, it has to be analyzed whether some unnecessary structural or parametrical elements are available which create costs but do not add a value.

It is now the task of a decision-maker to take the final decision on the supply chain design selection based upon performance and robustness estimations subject to his/her own risk perceptions. In cases having a zero resilience index value, the desired performance can be *attained* under any disturbances from the considered execution scenario. In other cases, there are some disturbances which may decrease the performance to an undesirable level. In Fig. 3.9, the intersect area is large in case (a) and 0 in case (b). Supply chain design #2 can be considered as a preferable option regarding the trade-off of performance vs resilience subject to the analyzed scenarios.

Remark Note that with the help of an attainable set, the resilience analysis is performed analytically but on the basis of an exact optimization-based model and for interval non-stationary perturbation data. With the help of the proposed method, the sophisticated scientific methodology, i.e., the attainable set can be used as an analytical solution to supply chain design resilience analysis.

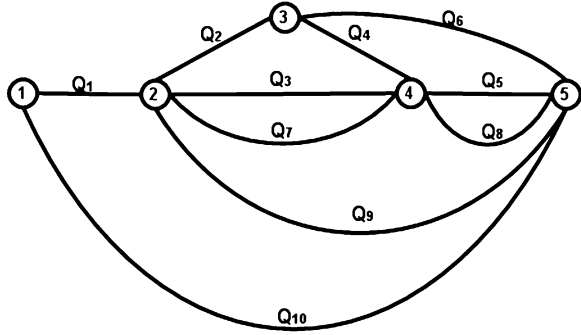
3.6 Fuzzy-Theoretic Analysis of Supply Chain Structural Robustness with the Help of Genome Method

3.6.1 Genome Method for Structural Robustness Analysis in the Supply Chain

The genome method has been developed in order to analyze robustness of different structures in dependence on the specifics of structure element connections and the failure probabilities (Kopytov et al. 2011; Ivanov et al. 2016c). The objective of the genome method application to the supply chain design is to include the structural properties of the supply chain design for robustness assessment with the use of failure probability estimations. In other words, the genome method can help to reveal the most efficient supply chain designs with the required level of robustness or the supply chain design with the highest possible robustness among alternative supply chain designs with similar efficiency. The next specific feature of the genome method is the usage of minimum structure failure edge-cuts that allow representing groups of critical suppliers or a critical supplier the failure of which interrupts the supply chain operation fully.

The structure genome $\chi = (\chi_0, \chi_1, \chi_2, \dots, \chi_n)$ is a vector that contains integer coefficients of the polynomial $T(Q) = \chi_0 + \chi_1 Q + \chi_2 Q^2 + \dots + \chi_n Q^n$ of the minimum structure failure edge-cut function, where Q is the failure probability of supply chain element (i.e., a supplier or a transportation channel). The minimum structure

Fig. 3.11 Supply chain design structure



failure edge-cut R_j means that in the case of a supply chain element failure in the edge-cut, the network becomes divided into two non-linked parts, with the source node in the first part and the target node in the second part. The minimum edge-cut identifies, in other words, a group of suppliers, the failure of which, will fully interrupt supply chain operations. This means that disruptions at the minimum structure failure edge-cut separate the supply chain into two non-connected parts and operations are interrupted.

Consider an example (see Fig. 3.11).

The simplified supply chain design structure in Fig. 3.11 comprises five nodes (nodes #1 and #5 are source and target respectively, i.e., node #1 is a raw material supplier, nodes #2, #3, and #4 are component suppliers, and node #5 is product assembly) and ten arcs (i.e., transportation channels). For this situation, where disruption may happen only on the arcs, the genome of this supply chain design includes 11 elements. If disruptions would also be considered as nodes, the genome would include 16 elements. For simplification of the explanation, we assume that the nodes are reliable and the failures are subject to the arcs only. In this case, for the given supply chain design, there are five minimum failure edge-cuts as follows (Eq. 3.18):

$$\begin{aligned}
 R_1 &= \{Q_1, Q_{10}\}, R_2 = \{Q_2, Q_3, Q_7, Q_9, Q_{10}\}, R_3 = \{Q_3, Q_4, Q_6, Q_7, Q_9, Q_{10}\}, \\
 R_4 &= \{Q_5, Q_6, Q_8, Q_9, Q_{10}\}, R_5 = \{Q_2, Q_4, Q_5, Q_8, Q_9, Q_{10}\}
 \end{aligned}
 \tag{3.18}$$

The failure polynomial for this supply chain design can be represented as Eq. (3.19):

$$\begin{aligned}
T(Q_1, Q_2, \dots, Q_{10}) = & Q_1 Q_{10} + Q_2 Q_3 Q_7 Q_9 Q_{10} \\
& + Q_3 Q_4 Q_6 Q_7 Q_9 Q_{10} + Q_5 Q_6 Q_8 Q_9 Q_{10} + Q_2 Q_4 Q_5 Q_8 Q_9 Q_{10} \\
& - Q_1 Q_2 Q_3 Q_7 Q_9 Q_{10} - Q_1 Q_3 Q_4 Q_6 Q_7 Q_9 Q_{10} - Q_1 Q_5 Q_6 Q_8 Q_9 Q_{10} \\
& - Q_1 Q_2 Q_4 Q_5 Q_8 Q_9 Q_{10} - Q_2 Q_3 Q_4 Q_6 Q_7 Q_9 Q_{10} \\
& - Q_2 Q_3 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} - Q_2 Q_3 Q_4 Q_5 Q_7 Q_8 Q_9 Q_{10} \\
& - Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} - Q_2 Q_4 Q_5 Q_6 Q_8 Q_9 Q_{10} \\
& + Q_1 Q_2 Q_3 Q_4 Q_6 Q_7 Q_9 Q_{10} + Q_1 Q_2 Q_3 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} \\
& + Q_1 Q_2 Q_3 Q_4 Q_5 Q_7 Q_8 Q_9 Q_{10} + Q_1 Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} \\
& + Q_1 Q_2 Q_4 Q_5 Q_6 Q_8 Q_9 Q_{10} + Q_2 Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} \\
& + Q_2 Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} - Q_1 Q_2 Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10} \\
& - Q_1 Q_2 Q_3 Q_4 Q_5 Q_6 Q_7 Q_8 Q_9 Q_{10}
\end{aligned} \tag{3.19}$$

or, in a more compact form as Eq. (3.20):

$$T(Q) = Q^2 + 2Q^5 - 4Q^7 - Q^8 + 5Q^9 - 2Q^{10}. \tag{3.20}$$

In the example in Fig. 3.11, we have $m = 5$, number of combinations from m for t ($t = 1, 2, 3, 4, 5$; i.e., the combination number for 1, 2, 3, 4, and 5 edge-cuts from five minimum edge-cuts) equals 5, 10, 10, 5, 1 respectively, $n = 10$ edges. The first five members in $T(Q_1, Q_2, \dots, Q_{10})$ (Eq. 3.19) correspond to $t = 1$ (i.e., the edge-cuts from five minimum edge-cuts). Next nine members in Eq. (3.19) with “−” are related to $t = 2$ (there should be ten members but one member is cancelled by “+” in $t = 3$). Next seven members with “−” are related to $t = 3$ (there should be ten members but one member is cancelled by “−” in $t = 2$ and two members are cancelled by “−” in $t = 4$). Finally, the last two members with “−” relate to $t = 4$ (there should be five members but two members are cancelled by “+” in $t = 3$ and one member is cancelled by “+” in $t = 5$).

Note that the compact form (3.20) of the polynomial (3.19) is only valid if $Q_1 = Q_2 = \dots = Q_n = Q$. The genome of this supply chain design is $\chi = (0, 0, 1, 0, 0, 2, 0, -4, -1, 5, -2)$. The interpretation of this genome is as follows:

- The supply chain design contains 10 transportation edges (vector dimensionality is $11 = 10 + 1$)
- The components of the genome change their operators (“+” and “−”) three times. This means we have three production sites in the supply chain (vertices #2, 3 and 4). Node #1 is a supplier, and node #5 is a customer
- The last genome component is “−2”. This means, that the graph has an edge to ensure the direct and return deliveries (i.e., the edge Q_4 is a “bridge” that makes it possible to deliver products from node #3 to #4 and return the trucks from #4)
- The first non-zero genome component “1” is the third one. This means that the supply chain design has one edge combination that contains two edges the failure of which would result in full supply chain destruction (i.e., the edges $\{Q_1, Q_{10}\}$).

- The second non-zero component is “2” and it is the sixth genome component. This means that the supply chain design has two edge combinations each of which contains five edges the failure of which would result in full supply chain destruction (i.e., $\{Q_2, Q_3, Q_7, Q_9, Q_{10}\}$ and $\{Q_5, Q_6, Q_8, Q_9, Q_{10}\}$).

In general, the following topological properties are contained in the genome (Ryabinin 1976; Colbourn 1987; Kopytov et al. 2011):

- the power of the lower polynomial member equals the minimal power among minimum structure failure edge-cuts (i.e., the number of the first non-zero genome component with $\chi_l > 0$ и $\chi_i = 0, \forall i < l$);
- the coefficient of the lower polynomial member is always positive and equals the number of the minimal-power minimum structure failure edge-cuts (i.e., $\chi_l > 0$ и $\chi_i = 0, \forall i < l$);
- the power of the highest polynomial member equals the number of the network elements.

3.6.2 Supply Chain Structural Robustness Computation: Exact Method

Consider a failure in the supply chain that leads to a change in the supply chain structure regarding i -elements ($i \leq n$, where n is the number of supply chain elements). If among all possible structural states C_n^i , the number of reliable states S_i for this failure can be determined, the structural robustness G_i can be computed as shown in Eq. (3.21):

$$G_i = \frac{R_i}{C_n^i} \quad (3.21)$$

The relation of disrupted states N_i ($N_i = C_n^i - R_i$) to all possible states determines the supply chain structure degradation (Eq. 3.22):

$$D_i = \frac{N_i}{C_n^i}. \quad (3.22)$$

To compute the supply chain structural robustness and degradation, the synthesis process of reliable and disrupted states needs to be investigated. Describe the supply chain structural robustness as a function (3.23)

$$\Psi(i) = G_i = \frac{S_i}{C_n^i} \quad (3.23)$$

For comparison of different supply chain design structures, we introduce the relative function of structural robustness $\Psi\left(i/n\right)=1-\frac{S_i}{C_n^i}$ within a discrete set of failures.

This function is subject to linear interpolation by a linear piecewise function $\hat{\Psi}(x), x \in [0, 1]$. Then, the integral functional of the supply chain structural robustness can be described as shown in Eq. (3.24).

$$F_g = \int_0^1 \hat{\Psi}(x) dx. \quad (3.24)$$

To compute the supply chain structural robustness, the number of disrupted states needs to be determined. Under the disrupted state, we understand the supply chain state if all the elements in at least one of the network minimum edge-cuts are disrupted. Consider two options:

- (a) The edge-cuts does not contain common elements
- (b) The edge-cuts contain common elements

For (a), the function of structural robustness can be defined as Eq. (3.25):

$$\Psi(i) = 1 - \frac{N_i}{C_n^i} = 1 - \frac{\sum_{j=1}^{\min\{\lfloor \frac{i}{m} \rfloor, k\}} (-1)^{j-1} C_k^j C_{n-jm}^{i-jm}}{C_n^i}, \quad (3.25)$$

where $\lfloor \frac{i}{m} \rfloor$ is the whole part of disrupted minimum edge-cuts.

Equation (3.25) is based on the calculation of the number of disrupted states as $N_i = C_k^j C_{n-jm}^{i-jm}$, where C_k^j is the number of combinations from k -minimum edge-cuts for j -number of the disrupted edge-cuts, C_{n-jm}^{i-jm} is the number of $n - jm$ elements subject to other disrupted elements $i - jm$.

For (b), the supply chain is characterized by k -minimal failure edge-cuts, each of which contains $m_j (j = 1, \dots, k)$ elements and the edge-cuts have common elements. In this case, the number of the disrupted states is defined according to Eq. (3.26)

$$\begin{aligned} N_i = & \sum_{j=1}^k \delta(i - m_j) C_{n-m_j}^{i-m_j} - \sum_{j_1=1}^k \sum_{j_2 > j_1}^k \delta(i - m_{j_1} - m_{j_2} + m_{j_1 j_2}) C_{n-m_{j_1}-m_{j_2}+m_{j_1 j_2}}^{i-m_{j_1}-m_{j_2}+m_{j_1 j_2}} + \\ & + \sum_{j_1=1}^k \sum_{j_2 > j_1}^k \sum_{j_3 > j_2}^k \delta(i - m_{j_1} - m_{j_2} - m_{j_3} + m_{j_1 j_2 j_3}) C_{n-m_{j_1}-m_{j_2}-m_{j_3}+m_{j_1 j_2 j_3}}^{i-m_{j_1}-m_{j_2}-m_{j_3}+m_{j_1 j_2 j_3}} - \dots \\ & \dots (-1)^{k-1} \delta(i - m_{j_1} - m_{j_2} - \dots - m_{j_k} + m_{j_1 j_2 \dots j_k}) C_{n-m_{j_1}-m_{j_2}-\dots-m_{j_k}+m_{j_1 j_2 \dots j_k}}^{i-m_{j_1}-m_{j_2}-\dots-m_{j_k}+m_{j_1 j_2 \dots j_k}}. \end{aligned} \quad (3.26)$$

where $m_{j_1 j_2 \dots j_k}$ is the total number of common elements in the minimum disrupted edge-cuts with the numbers $j_1, j_2, \dots, j_k$.

Using Eqs. (3.25) and (3.26), the supply chain structural robustness can be computed subject to Eq. (3.19). If the area under the interpolated function of

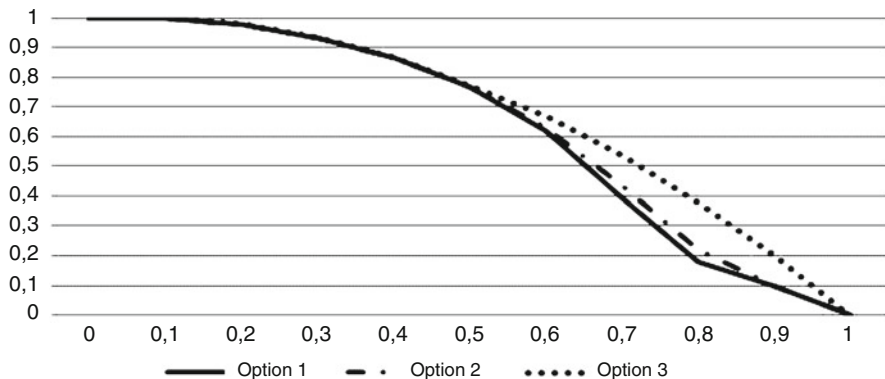


Fig. 3.12 Relative estimations of supply chain structural robustness

structural robustness equals $\hat{\Psi}(x) = 1$, no disrupted states exists and the supply chain structure can be classified as fully reliable or excessive. The area between $y = \hat{\Psi}(x)$ and $y = 1$ can be considered as the value of supply chain structure degradation.

The calculation of the minimum failure edge-cuts has been proved to be NP-hard. Therefore, the computing of the supply chain structural robustness according to Eqs. (3.19) and (3.22) is a complex combinatorial problem. In following, we suggest simple heuristic methods for calculation of the upper and lower bounds of supply chain structural robustness.

3.6.3 Computation of the Upper and Lower Boundaries for Supply Chain Structural Robustness

3.6.3.1 Computation of the Upper Boundary for Supply Chain Structural Robustness

Recall that the first non-zero genome component $\chi_r, r > 0$ equals the number of minimum failure edge-cuts of the power r , and the genome dimensionality equals the number of supply chain elements. In this case, Eqs. (3.21) and (3.22) can be used to compute the upper boundary of supply chain structural robustness. Consider the supply chain design example in Fig. 3.11. The genome of this supply chain design is $\chi = (\chi_0, \chi_1, \chi_2, \dots, \chi_n) = (0, 0, 1, 0, 0, 2, 0, -4, -1, 5, -2)$. This means that the supply chain design structure has a minimum edge-cut of the power 2 and two minimal edge-cuts of the power 5. In total, there are five minimum edge-cuts in this structure: $R_1 = \{Q_1, Q_{10}\}, R_2 = \{Q_2, Q_3, Q_7, Q_9, Q_{10}\}, R_3 = \{Q_3, Q_4, Q_6, Q_7, Q_9, Q_{10}\}, R_4 = \{Q_5, Q_6, Q_8, Q_9, Q_{10}\}, R_5 = \{Q_2, Q_4, Q_5, Q_8, Q_9, Q_{10}\}$ One edge-cut is to the power of 2, two edge-cuts are to the power of 5, and two edge-cuts are to

the power of 6. The minimum edge-cuts have common elements. The edge-cut R_1 has a common element Q_{10} , with all other edge-cuts the edge-cut R_2 has with the edge-cuts R_3, R_4, R_5 the common elements $\{Q_3, Q_7, Q_9, Q_{10}\}, \{Q_9, Q_{10}\}, \{Q_2, Q_9, Q_{10}\}$, the edge-cut R_3 has with the edge-cuts $R_4, R_5 - \{Q_6, Q_9, Q_{10}\}, \{Q_4, Q_9, Q_{10}\}$, and R_4 has with the edge-cut R_5 the common elements $\{Q_5, Q_8, Q_9, Q_{10}\}$.

Compute the relative supply chain structural robustness subject to three data sets (see Fig. 3.12):

1. Full number of minimum edge-cuts (Eq. 3.22 used)
2. Edge-cut to the power of 2 and two edge-cuts to the power of 5 (Eq. 3.22 used)
3. Only edge-cuts to the power of 2 (Eq. 3.21 used)

Using the functional $F_g = \int_0^1 \hat{\Psi}(x)dx$, we compute the integral supply chain structural robustness. The upper boundary for the option (3) is

$$F_g^{<2>} = \int_0^1 \hat{\Psi}^{<2>}(x)dx = 0.744, \quad \text{for the option} \quad (1)$$

$$F_g^{<2,5,6>} = \int_0^1 \hat{\Psi}^{<2,5,6>}(x)dx = 0.695, \quad \text{and for options} \quad (2)$$

$$F_g^{<2,5>} = \int_0^1 \hat{\Psi}^{<2,5>}(x)dx = 0.705.$$

It can be observed that compared to the real supply chain structural robustness (option 1), the error for option (2) is 1.4% and for the option (3) – 8.6%. In general, the error depends on the number of supply chain elements and increases with the increase in the supply chain element number. However, the proposed method allows fast computation of the upper boundaries for supply chain structural robustness.

3.6.3.2 Approximated Lower Boundary of Supply Chain Structural Robustness

According to the duality principle, the polynomials of the reliable and disrupted supply chain modes are interconnected as $R(P) + T(Q) = 1$, where $P + Q = 1$ (the failure polynomial depends both on P and Q; since $Q = 1 - P$, it becomes possible to re-write the failure polynomial for P or Q only). The components of the structure genome $\chi = (\chi_0, \chi_1, \chi_2, \dots, \chi_n)$ are the coefficients of the polynomial $T(Q) = \chi_0 + \chi_1 Q + \chi_2 Q^2 + \dots + \chi_n Q^n$. Consider the dual structure genome $\eta = (\eta_0, \eta_1, \eta_2, \dots, \eta_n)$ that is composed of the coefficients of the reliable structure polynomial $R(P) = \eta_0 + \eta_1 P + \eta_2 P^2 + \dots + \eta_n P^n$. The structure genome contains the

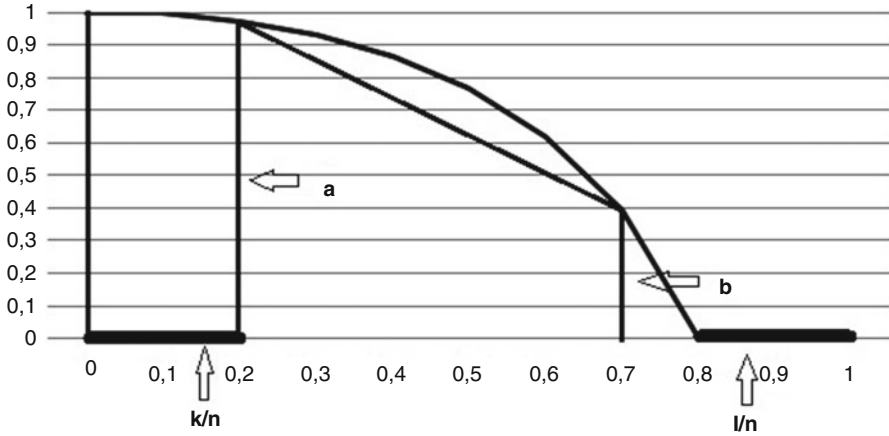


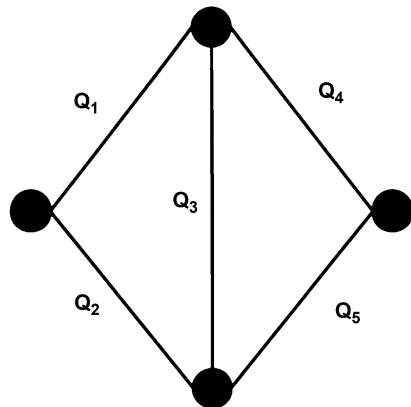
Fig. 3.13 Computation of the lower boundaries for supply chain structural robustness

characteristics of the minimum failure edge-cuts. The dual genome contains the characteristics of the minimal paths for non-disrupted execution in the network. The first non-zero component of the dual genome $\eta_l, l > 0$ equals the number of minimal paths of the power l . Using the genome and its dual analogous, it becomes possible to calculate the approximated supply chain structural robustness as shown in Fig. 3.13.

The first non-zero genome components makes it possible to compute $a = 1 - \frac{\chi_k}{C_n^k}$ and $b = \frac{\eta_l}{C_n^l}$. Then the approximated lower boundaries for supply chain structural robustness can be computed according to Eq. (3.27)

$$\begin{aligned} \hat{F}_g &= \frac{k-1}{n} + \frac{1+a}{2} \cdot \frac{1}{n} + \frac{a+b}{2} \cdot \frac{n-k-l}{n} + \frac{b}{2} \cdot \frac{1}{n} = \frac{2k-1}{2n} \\ &+ \left(1 - \frac{\chi_k}{C_n^k} + \frac{\eta_l}{C_n^l}\right) \cdot \frac{n-k-l+1}{2n}, \text{ } \forall \chi_k > 0, \chi_i \\ &= 0 \quad \forall 0 < i < k; \eta_l > 0, \chi_j = 0 \quad \forall 0 < j < l \end{aligned} \quad (3.27)$$

The genome and the dual genome from Fig. 3.11 equal $\chi = (\chi_0, \chi_1, \chi_2, \dots, \chi_n) = (0, 0, 1, 0, 0, 2, 0, -4, -1, 5, -2)$, $\eta = (\eta_0, \eta_1, \eta_2, \dots, \eta_n) = (0, 1, 1, 4, -10, -12, 56, -72, 46, -15, 2)$, respectively. Therefore $\chi_k = 1$, $k = 2$, $\eta_l = 1$, $l = 1$, $n = 10$. The approximated supply chain structural robustness is $\hat{F}_g = \frac{3}{20} + \left(1 - \frac{1}{45} + \frac{1}{10}\right) \cdot \frac{8}{20} = 0.581$. For this example, this is also the lower bound of the supply chain structural robustness.

Fig. 3.14 Sample structure

3.6.4 Computation Example

Consider as an example of a supply chain structure a graph with parallel and cycle paths (Fig. 3.14).

The genome of this structure is $\chi = (0, 0, 2, 2, -5, 2)$. The minimum edge-cuts are $\{Q_1, Q_2\}$, $\{Q_4, Q_5\}$, $\{Q_1, Q_3, Q_5\}$, $\{Q_2, Q_3, Q_4\}$. They have common elements.

Using Eqs. (3.21) and (3.22), we get $F_g^{<2,2>} = \int_0^1 \hat{\Psi}^{<2,2>}(x) dx = 0.54$ as approximated supply chain structural robustness and $F_g^{<2,3>} = \int_0^1 \hat{\Psi}^{<2,3>}(x) dx = 0.5$ as

absolute robustness value (see Fig. 3.15).

Subject to Eq. (3.23) and dual genome $\eta = (\eta_0, \eta_1, \eta_2, \dots, \eta_n) = (0, 0, 2, 2, -5, 2)$, $\chi_k = 2$, $k = 2$, $\eta_l = 2$, $l = 2$, $n = 5$ and $\hat{F}_g = \frac{3}{10} + \left(1 - \frac{1}{5} + \frac{1}{5}\right) \cdot \frac{1}{5} = 0.5$.

3.6.5 Advanced Analysis with Costs Considerations

In this section, we extend the analysis towards the trade-off “robustness vs. efficiency”. In particular, for analysis, we consider four supply chain network structures from the study by Kim et al. (2015) (Fig. 3.16):

For these structures, we first compute the supply chain structural robustness. In the second step, two hypotheses regarding supply chain design are formulated:

Hypothesis 1 Even if the number of supply chain elements in different supply chain design structures is equal, the robustness of these structures can be different.

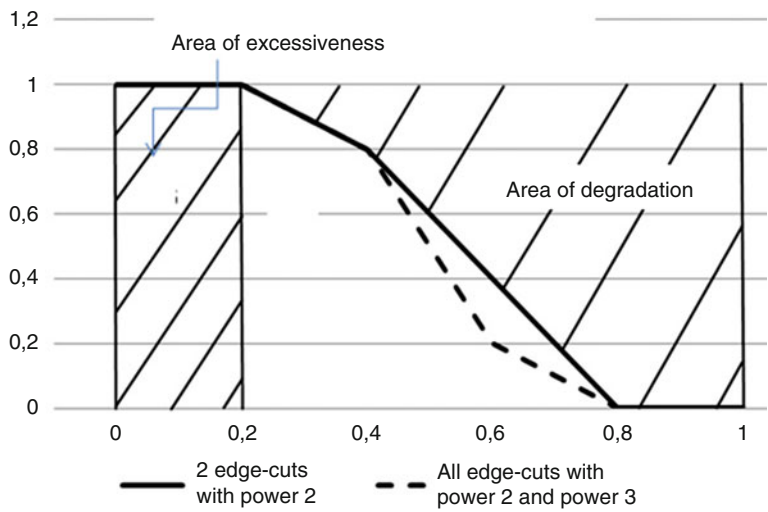


Fig. 3.15 Robustness analysis results

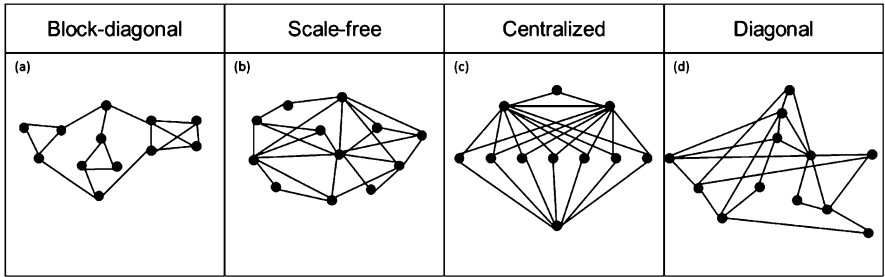


Fig. 3.16 Referenced supply chain network structures (Adopted from Kim et al. 2015)

Kim et al. (2015) concluded in their study that the form of a supply chain structure influences supply chain robustness rather than the number of elements in the supply chain. This is a relevant point regarding “robustness vs. efficiency”. In this regard, we assume that the higher the number of supply chain elements, the higher the investments in supply chain protection and the lower the efficiency.

Hypothesis 2 The investments in the extension of a supply chain structure can potentially increase its robustness but this increase is not always proportional.

According to (Kim et al. 2015), “redundancy by adding extra nodes or arcs may not improve the resilience of the network.” Redundancy is a well-known robustness reserve that helps to increase supply chain capacity and flexibility. For example, in case of a disruption at supplier A, alternative supplier B could be used to ensure that the supply chain survives during the recovery period at supplier A. However such redundancies not only increase robustness but also costs. In order to analyze this hypothesis, we will extend the referenced structure from Kim et al. (2015) by one node and four arcs.

For costs analysis, Eq. (3.28) is used:

$$K = (n \times k_n) + (n_e \times k_e) + \left[\left(\sum_j^n n_{ji} \right) \times k_{ji} \right] + \left[\left(\sum_i^n n_{ij} \right) \right] \times k_{ij} \quad (3.28)$$

where

K is total costs

n is the number of nodes in the graph

n_e is the number of arcs in the graph

n_{ji} is the number of incoming arcs for node j

n_{ij} is the number of outgoing arcs for node j

k_n is the cost of having a node in the graph, assumed as \$100

k_e is the cost of having an arc in the graph, assumed as \$10

k_{ji} is the cost of having an incoming arc for node j , assumed as \$20

k_{ij} is cost of having an outgoing arc for node j , assumed as \$20

3.6.5.1 Robustness Analysis

For structure (a), the structure genome and the dual genome are as follows:

$$\begin{aligned} X_a &= (\chi_0, \chi_1, \chi_2, \dots, \chi_n) = (0, 0, 0, 64, -192, 19, 694, \\ &\quad -1514, 4744, -19452, 49202, -62609, -8598, 2045443, \\ &\quad -458498, 615485, -561155, 328223, -62623, \\ &\quad -105271, 145674, -109189, 57806, -22879, 6813, \\ &\quad -1494, 229, -22, 1), \\ \eta_a &= (\eta_0, \eta_1, \eta_2, \dots, \eta_n) = (0, 0, 0, 0, 0, 3, 0, 4, -4, 1, \\ &\quad -7, 4, -9, 8, -7, 19, -15, 16, -20, 16, -15, 8, \\ &\quad -7, 13, -13, 14, -13, 6, -1) \end{aligned}$$

Since $k = 3, \chi_k = 64, l = 5, \eta_l = 3, n = 28$, then

$$\hat{F}_g^a = \frac{5}{56} + \left(1 - \frac{64}{C_{28}^3} + \frac{3}{C_{28}^5} \right) \cdot \frac{21}{56} = 0.457$$

The supply chain structural robustness for the structures b, c, and d are as follows:

$$\hat{F}_g^b = 0.4998, \hat{F}_g^c = 0.4829, \hat{F}_g^d = 0.4671$$

Similar to Kim et al. (2015), we assumed that the node #1 (Sink) and node #12 (Source) are not perturbed. In Table 3.1, the results are compared with the resilience estimation from Kim et al. (2015).

Table 3.1 Comparison of the values of supply chain network robustness

Structure	Robustness values	
	Kim et al. (2015)	Our approach
a	0.11	0.46
b	0.30	0.50
c	0.16	0.48
d	0.13	0.47

Table 3.2 Costs analysis

	Block-diagonal	Scale-free	Centralized	Diagonal
Number of nodes	12	12	12	12
Number of arcs	18	25	29	25
Number of incoming arcs	18	25	30	25
Number of outgoing arcs	18	25	30	25
Total costs	2100	2450	2690	2450

By comparing the results of the two methods, it can be observed that both methods suggest the same order of the robust supply chain design: $B \rightarrow C \rightarrow D \rightarrow A$. At the same time, in the study by Kim et al. (2015), the supply chain design #B has a significant higher robustness as compared to three other structures. In our analysis, the robustness of different supply chain structures is closer to each other. The explanation of these effects can be seen in the inclusion of the minimum edge-cut failures in the genome instead of individual failures in the robustness analysis. This is the benefit and novelty of the proposed approach. The second difference is basically higher robustness values in our approach. This insight requires more analysis efforts since the methods for robustness computations in both bodies of work have been different.

3.6.5.2 Costs Analysis

According to Eq. (3.28), the following costs have been calculated for the initial structures from Kim et al. (2015) with regards to Hypothesis 1 (Table 3.2).

According to Hypothesis 2, we extend the initial structure of the diagonal supply chain design by one node and four arcs (Fig. 3.17).

The following costs and supply chain structural robustness have been calculated for the extended diagonal structure according to Hypothesis 2 (see Table 3.3; for other structures, similar correlations have been obtained).

It can be observed from Table 3.3 that the introduction of a back-up supplier in the supply chain results in an increase in costs of about 11% whilst the robustness is increased by 2% only. Therefore it can be observed that the investments in an extension of the supply chain structure can potentially increase its robustness but this increase is not always proportional.

Tables 3.1 and 3.2). In our case, the most reliable structure is supply chain design B (scale-free) while the most expensive one is the centralized structure (C) with quite lower supply chain design robustness. At the same time, it can be observed that the most efficient supply chain design (A) is also the most fragile when experiencing possible disruptions. We can conclude that the relationship between supply chain design robustness and efficiency depends more on the form of supply chain design structure than on the number of the supply chain elements and their structure excessiveness. This implies that the increase of supply chain robustness should not always be achieved only by additional investments in new facilities and logistics. Supply chain design structure reconfiguration may be another promising option.

It can be concluded based upon this example and data that the supply chain design structure extension (e.g., in the form of dual or multiple sourcing) contributes to an increase in both supply chain robustness and costs. However, *the investments in the extension of the supply chain structure can potentially increase its robustness but this increase is not always proportional*. The suggested method can be used by supply chain managers to estimate the trade-off of “robustness vs efficiency” and to get an overall view on this constellation in the supply chain.

3.7 Models and Algorithms of Supply Chain Reconfiguration

3.7.1 Decision Making Framework for Resilience Supply Chains

Let's consider the general conceptual scheme of decision making on resilient supply chains (see Fig. 3.18).

On the basis of the goals set at higher levels of a supply chain, plans are formed. During supply chain functioning, the conformity of the actual course of events with the planned values is analyzed. In the case of deviations (negative perturbation impacts), the necessary managerial influences (positive control influences) on the correction of processes and plans for supply chain configuration upgrades will be taken. The given scheme describes the basic functions of supply chain management under conditions of interaction with a perturbed environment. Such a scheme can be realized on each of three levels of decision-making (strategic, tactical and operative). The interrelation of these three management levels is very important since it allows us to realize the construction of realistic plans balanced with each other and to provide feedback for the adaptation of these plans taking into account real performance of supply chain processes. Let us consider a concrete example of the analysis of perturbation influences and the adaptation of a supply chain.

As a result of the perturbation influence “Delay in delivery from the supplier”, the supply chain can appear inefficient or in a disabled state. In the case of a disabled condition, it is a question of a disturbance in the performance of the supply

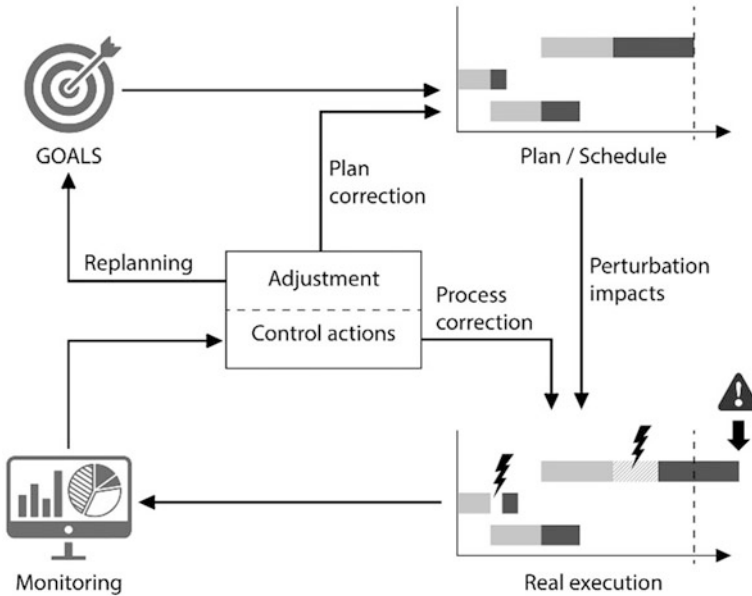


Fig. 3.18 Supply chain planning system with positive and negative feedback (From Ivanov 2010)

chain function “Start manufacturing a product lot” owing to the absence of materials (a deviation in the parameter “Start term of manufacturing”). Further, this disturbance can be classified as a disruption or deviation.

In the case that the broken function nevertheless can be executed (i.e. the parameter “End term of manufacturing a product lot” does not deviate from the planned value) without correcting managing influences, for example, on the basis of the safety stock use, it is a question of *deviation*. If the function can be executed only with the application of control influences, it is a question of *disruption*, which should be eliminated on the basis of managerial decisions on the recovery of an efficient supply chain state (for example, process corrections on the basis of the urgent material acquisition from other suppliers; see parametrical adaptation).

In the case of the impossibility of performance of all the planned orders according to the goals (delivery time, costs, quality), *plan correction*, for example, the redistribution of the resources between various orders, the attraction of additional suppliers, etc. is necessary. If there is a situation of plan disruption, goal adaptation is necessary, i.e. *re-planning* (for example, changes in delivery times). An extreme case of failure is a catastrophic situation, where recovery of the supply chain plans (at all three levels of management) is impossible and a new strategy and control system for the supply chain is necessary. In this case, it is possible to talk about the loss of supply chain resilience.

3.7.2 Algorithms of Supply Chain (Re)Planning Under Uncertainty

3.7.2.1 General Algorithm of Supply Chain Planning

Let us consider the general logic scheme of decision making on the choice of a supply chain plan, taking into account supply chain reliability and flexibility. It consists of 10 steps, which will be considered below.

Step 1. The uncertainty analysis and risks identification

In the first step, a decision maker analyses the uncertainty and identifies the risks. Methods of risk management can be widely used in this step.

Step 2. The risks analysis in a supply chain

At this stage, there is a linkage of the identified risks to concrete parts and events in a supply chain. The influence of risk on a supply chain, in particular on key operations in a supply chain, will be defined along with revealing critical stages and operations in a supply chain. The given analysis can be realized on the basis of expert methods and with the use of the sensitivity theory.

Step 3. The development of managerial actions scenarios in the case of disturbances in a supply chain

At the given stage, the revealed “bottlenecks” in a supply chain and the potential perturbation influences are brought into correspondence with certain control influences. Scenarios of the actions of managers (for example, as event management plan) are developed here.

Step 4. Introduction of redundancies for the supply chain strengthening

The given stage is intended for the creation of certain reliability and flexibility reserves (safety stocks, reserve channels, a pool of alternative suppliers, a system of information coordination, the formation of a set of not final decisions) for the supply chain strengthening, especially its bottlenecks and key operations. A range of supply chain variants with different levels of redundancy are under construction empirically, each of which is estimated in the following stage.

Step 5. Supply chain resilience analysis

At the given stage, there is an estimation of different supply chain configuration and plans to different areas of robustness and adaptability under the influence of different areas of perturbation influences.

The stability analysis allows the definition of the admissible borders of deviations in supply chain execution parameters and of the possibility of returning the supply chain to a planned (or wished for) state after disturbance. As a result, some zones of resilience are defined, to each of which there corresponds a certain level of necessary control influences.

Various deviations from the ideal parameter values correspond to three classes of supply chain states: the supply chain state is stable and no adjustments are needed, the supply chain state is stable, but adjustments are needed, and the supply chain has lost its stability, the final goal cannot be achieved any more under the current conditions, i.e. considering a fixed variety of possible adjustment actions, a certain period of time, and a certain set of deviations as well as algorithm stability. Such an analysis must be performed for each execution parameter at all the relevant instants of time and regarding each final goal. In simple issues it can be realized via expert methods and analytical algorithms.

Step 6. An estimation of costs for the elimination of redundancies and disturbances

At the given stage, there is a cost estimation of various measures for the strengthening and adaptation of supply chains. The block of costs for the maintenance of supply chain reliability and flexibility along with the “productive” costs (e.g., the total costs of ownership) form the basis for an estimation of cumulative costs in a supply chain as a result.

On the basis of expert methods, there is an elimination of part of the alternative plans considered in stage 5 (for example, owing to unrealistic costs for the robustness and flexibility maintenance or plans with an unacceptably level of resilience).

Step 7. The formation of a set of alternative supply chains

At the given stage, the set of alternative supply chains received after the performance of step 6 is formed.

Step 8. The final analysis of the supply chain resilience

The same as in step 5, but on a narrowed set of alternatives and taking into account costs for supply chain reliability, flexibility, and adaptation.

Step 9. The results’ calculation and analysis according to the supply chain economic performance and stability

The given stage consists of the analysis of alternative supply chains generated in step 8 concerning the level of supply chain economic performance and resilience. The results’ calculations and analyses according to the supply chain economic performance and resilience can be represented in the form of Table 3.4.

Each of the estimated alternative supply chains as a result is characterized by certain indicators of profitability and resilience. Table 3.4 reflects the results with regard to one level of control impacts and one level of perturbation impacts.

Step 10. The final choice of a supply chain configuration or plan

The final choice of a supply chain configuration or plan occurs on the basis of managerial individual preferences and the risk perception.

Table 3.4 The simple analysis of alternative supply chain designs

	Revenue	Costs	Profit	Resilience	Profit in the worst case
Supply chain 1	J ₁₁	J ₂₁	J ₃₁	J ₄₁	J ₅₁
Supply chain 2	J ₁₂	J ₂₂	J ₃₂	J ₄₂	J ₅₂
Supply chain 3	J ₁₃	J ₂₃	J ₃₃	J ₄₃	J ₅₃

3.7.2.2 Control Algorithms of Supply Chain Parametric and Structural Reconfiguration

The input data for the supply chain adaptation is gathered during the supply chain functioning at the state $S_{\delta-1}$ and is received for the state S_{δ} . Thus, we obtain the formulas (3.28 and 3.29):

$$J_G = J_G(\mathbf{x}(t), \mathbf{u}_{pl}(t), \mathbf{v}(\mathbf{x}(t), \xi), \xi) \rightarrow \max_{\mathbf{u} \in \Delta}, \quad (3.29)$$

$$\Delta = \mathbf{Q}(\mathbf{x}(t)) \times \mathbf{V}(\mathbf{x}(t), \xi, t), \quad \mathbf{u} = \mathbf{u}_{pl}(t) \times \mathbf{v}(\mathbf{x}(t), \xi), \quad (3.30)$$

where $\mathbf{x}(t)$ is a state vector and $\mathbf{u}_{pl}(t)$ is the main vector of control inputs, in other words, it is a control program for the supply chain dynamics, $\mathbf{v}$ is a vector of control inputs compensating for perturbation impacts over the control program, $\mathbf{Q}(\mathbf{x}(t))$ and $\mathbf{V}(\mathbf{x}(t), \xi, t)$ are the sets of allowable controls $\mathbf{u}_{pl}(t)$ and $\mathbf{v}(\mathbf{x}(t), \xi)$, respectively and $\xi(t)$ is a vector of perturbation impacts, where $\xi(t) \in \Xi(\mathbf{x}(t), t)$.

The general performance metric of the forecasted states can be evaluated as a functional of the enumerated values via simulation experiments with a supply chain operation model. In this case, the following group of tasks is substituted for the initial problem of the supply chain control:

$$J_G = J_G(\mathbf{x}(t, \lambda'), \mathbf{u}_{pl}(t, \lambda'), \mathbf{v}(\mathbf{x}(t, \lambda'), \xi), \xi) \rightarrow \max_{\lambda' \in \Delta'}, \quad (3.31)$$

$$\Delta' = \{\lambda' | \mathbf{u}_{pl}(t, \lambda') \times \mathbf{v}(\mathbf{x}(t, \lambda'), \xi) \in \mathbf{Q}(\mathbf{x}(\lambda')) \times \mathbf{V}(\mathbf{x}(\lambda'), \xi)\}, \quad (3.32)$$

$$\sum_{\bar{g} \in \Gamma'} \lambda'_{\bar{g}} J_{\bar{g}}(\mathbf{x}_{\bar{g}}) \rightarrow \max_{\mathbf{x}_{\bar{g}} \in D_{\bar{g}}(T_f, T_0, \mathbf{x}_{\bar{g}}(T_0))} \text{extr}, \quad (3.33)$$

$$\sum_{\bar{g} \in \bar{L}} \lambda'_{\bar{g}} = 1, \quad \lambda'_{\bar{g}} \geq 0, \quad \mathbf{x}_{\bar{g}} = \left\| \mathbf{x}^{(\bar{g})T} \mathbf{x}^{(o)T} \right\|^T, \quad \bar{g} \in \bar{L} = \{g, k, f, p, e, \nu, c\}. \quad (3.34)$$

Here, the vectors $\mathbf{x}_{\bar{g}}(T_f)$ returning optimal values are sought, while the vector $\lambda'_{(rr)}$ is fixed ($rr = 0, 1, 2, \dots$ is the number of the current iteration). The received problems of mathematical programming have several important features. The search for components of the vector $\mathbf{x}_{\bar{g}}^{(rr)}$ can be fulfilled over subsets of the attainable set $D_{\bar{g}}(T_f, T_0, \mathbf{x}_{\bar{g}}(T_0))$ rather than over the whole sets of allowable alternatives. The subsets include non-dominated alternatives of the enumerated models. The non-dominated alternatives can be received via the orthogonal projection of the goal sets to the attainable set $D_{\bar{g}}(T_f, T_0, \mathbf{x}_{\bar{g}}(T_0))$. Each particular model

includes the state vector $\mathbf{x}^{(o)}$ of the operation model $M_{<o>}$ besides its own state vectors $\mathbf{x}^{(g)}$, $\mathbf{x}^{(k)}$, ..., $\mathbf{x}^{(c)}$. The above-mentioned structural features of Eqs. (3.30), (3.31), (3.32), and (3.33) allows us using decomposition and overcome the problem of high dimensionality.

When the vector $\mathbf{x}\bar{\delta}^{(rr)}(T_f)$ is known, the optimal programs $\mathbf{u}_{pl}^{(rr)}(t, \lambda'_{(rr)})$ for the supply chain control can be defined within each model $M_{\bar{g}}$ via numerical methods (for example, via Krylov and Chernousko's method) (Chernousko 1994). The programs $\mathbf{u}_{pl}^{(rr)}(t, \lambda'_{(rr)})$ are used for the evaluation of a new approximation of the vector $\lambda'_{(rr+1)}$ in the simulation model $M_{\bar{g}}$ describing the supply chain functioning under perturbation impacts.

The problem of the λ^* search is similar to the problem of optimal experiment design. Here, elements of the vector λ' are endogenous variables and the performance metric (Eq. 3.31) is an exogenous one. Different methods can be used for the optimal design of experiments, for example the method of quickest ascent, the methods of random search, the method of ψ -transformation (Chichinadze 1980). In conclusion, we note that components of the vector λ' can define the preferable control inputs $\mathbf{v}(\mathbf{x}(t, \lambda'), \xi)$ for the compensation of the mismatch of the planned trajectory of supply chain dynamics with the predictable (via simulation) trajectory.

The matching of simulation and analytical models is based on the Pareto principle by means of iterations during the process of information exchange. This approach is based on the assumption that the global extremum of the generalized quality level of the performance of supply chain execution is situated in one of the points of Pareto's set, defined by certain quality levels, obtained by means of non-formal decomposition of the problem (and corresponding simulation model).

As a matter of fact, this assumption is fulfilled when we deal with a monotone utility function as a function of particular performance metrics. Besides, multi-criteria optimization is performed by means of different types of models. The narrowing of Pareto's set in discrete models is performed in the interactive mode by means of eliminating elements from this set. The elimination is based upon the mathematical investigations of Pareto's set features and the consideration of decision-makers' opinions (evaluation of the set's power, of the performance metrics' range, and of the performance metrics' contradictoriness).

If the power of Pareto's set becomes acceptable, then the supply chain structures selected on the base of static models can be checked by means of queuing theory models and then by means of simulation models. If the constraints characterizing the models are not fulfilled, then the corresponding structure variants are no longer considered.

The supply chain synthesis process is finalized with the search for appropriate programs for developing supply chain structures (that is, programs promoting the existing supply chain structures to advanced ones).

Finally, let us consider two groups of algorithms for structural adaptation of supply chain structural dynamics control models. All the algorithms are based on the choice of model structure for a given set of possible models. The algorithms of the first group use the procedures of fuzzy clusterization.

The second group of algorithms for structural adaptation of supply chain structural dynamics control models is based on the evolutionary (genetic) approach. Let us exemplify these algorithms in the structural adaptation of a model describing the structure dynamics of one supply chain output characteristic (of one element of the vector $\mathbf{y}(t_{<k>})$).

The residual of its estimation via the model M_θ , as compared with the observed value of the characteristic, can be expressed in Eq. (3.35) (Rastrigin 1981):

$$Q_{<k>}^{<\theta>} = [\tilde{\psi}_{<\theta,k>}(\mathbf{x}(t_{<k>} - 1), \mathbf{u}(t_{<k>}), \boldsymbol{\xi}(t_{<k>}), \boldsymbol{\beta}_\theta, t_{<k>}) - \tilde{y}(t_{<k>})]. \quad (3.35)$$

To simplify the formulas, we assume that the perturbation influences $\boldsymbol{\xi}(t)$ are described via stochastic models. Thus, the following performance metric can be introduced for the model M_θ :

$$\bar{Q}_{<k>}^{<\theta>} = \sum_{k=1}^K g^{(K-k)} Q_{<k>}^{<\theta>}, \quad (3.36)$$

where $0 \leq g^{(K-k)} \leq 1$ is a “forgetting” coefficient that “depreciates” the information received in the previous steps (control cycles). If $g^{(K-k)} = 0$ then $\bar{Q}_{<k>}^{<\theta>} = Q_{<k>}^{<\theta>}$, i.e. the weighted residual is equal to one received in the last step, as the prehistory has been “forgotten”. The coefficient $g^{(K-k)}$ was substituted for the function $f(K)$:

$$\bar{Q}_{<k>}^{<\theta>} = \sum_{k=1}^K f(K-k) Q_{<k>}^{<\theta>}, \quad \theta = 1, \dots, \theta. \quad (3.37)$$

Here, $f()$ is a monotone decreasing function of “forgetting”. It has the following properties:

$$f(\alpha) > 0, \quad f(0) = 1, \quad \lim_{\alpha \rightarrow \infty} f(\alpha) = 0, \quad f(\alpha) \geq f(\alpha + 1), \quad \alpha = 0, 1, \dots \quad (3.38)$$

Now, the structural adaptation algorithm is reduced to a search for the structure M_{θ^*} , such that

$$\bar{Q}_{<k>}^{<\theta^*>} = \min_{\theta=1, \dots, \theta} \bar{Q}_{<k>}^{<\theta>}. \quad (3.39)$$

Thus, it is necessary to calculate the performance metrics (Eq. 3.39) for all the competitive structures M_θ , $\theta = 1, \dots, \theta$ of supply chain structural dynamics control models at each control cycle $k = 1, \dots, K$. All the performance metrics should be compared, and the structure M_{θ^*} with the best measure (minimal residual) should be chosen.

The parametric adaptation of the model M_{θ^*} should follow the structural one. It is important to determine a proper “forgetting” function under the perturbation impacts $\boldsymbol{\xi}(t)$. The higher the noise level in the supply chain, the slower the decrease of the function should be implemented. However, if the supply chain greatly

changes its structure, then the function $f(\alpha)$ should decrease rapidly in order to “forget” the results of the previous steps. It can be shown that the structural-adaptation algorithms based on the model construction (synthesis) of atomic models (modules) are rather similar to the algorithms of the supply chain structural-functional synthesis. These algorithms only differ in the interpretation of the results.

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Chapter 4

Principles and Methods of Model-Based Decision-Making in the Supply Chain

4.1 Basics of Model-Based Decision-Making in Supply Chain Management

4.1.1 Problems, Systems, and Decision-Making

Decision-making is the major activity of supply chain managers. Each decision implies analytical and empirical components. Analytical methods play, therefore, a crucial role in supply chain decision-making methodologies (Kotzab et al. 2005; Dolgui and Proth 2010; Schonberger 2011; Render et al. 2012; Yalaoui et al. 2012; Stadler et al. 2015). In this Chapter, we describe principles and methods of model-based decision-making in the supply chain.

For a *problem* to exist there must be an individual (or a group of individuals), referred to as the problem owner (decision maker) that:

- is dissatisfied with the current state of affairs within a real-life context, or has unsatisfied present or future needs, i.e. has goals to be achieved or targets to be met;
- is capable of judging when these goals, objectives, or targets have been met to a satisfactory degree; and
- has control over some aspects of the problem situation that affect the extent to which goals, objectives, or targets can be achieved (Daellenbach and McNickle 2005).

Rather than assume that we have a well-structured problem with clearly defined objectives and alternative courses of action, it is better to:

- represent the problem situation where the issues are still vague, fuzzy
- gain a more comprehensive understanding of the various issues involved in decision-making

- formulate the right problem that ensures an appropriate level of detail to provide insights into the problem solution
- perform decision-making within the context of systems.

Most problems exist in a system context. A *System* is a set of interrelated entities, comprising a whole unity where each component interacts with or is related to at least one other component and they all serve a common objective. The *Environment* is the aggregate elements that do not belong to the system but influence it.

One of the basic system characteristics is its structure. The *Structure* is characteristic of steady links and interaction modes of system's elements. Structure determines the system's integrity, basics and building of organization and functioning. Structure is a framework of a system. In practice, many supply chain structures can be disrupted (e.g., Toyota's supply chain was badly affected by the tsunami in March 2011). Therefore, we can talk about supply chains' *structural dynamics* (Ivanov and Sokolov 2010).

Dynamics is a system's change and evolution in the form of changes in object and process states in space and time as driven by perturbation and control influences of both planned nature, e.g., to transit from a current state to a desired one, and adaptation nature, e.g., to adapt a system to a changed execution environment.

Decision is a selection of an activity or a set of activities to handle from several alternatives. Decisions are subject to constraints, which limit decision choices and objectives making some decisions more preferable than others do. The selection of a managerial decision leads the system goal-oriented to the output performance. The decisions shape the system behaviour concerning a certain individual goal or multiple goals. Objectives and criteria play the most important role in taking decisions.

Performance is a complex characteristic of the goal results of the system's functioning; potential and real performance, taking into account the conformity of the achieved results with the goals set by management at the planning stage. Performance is measured with certain metrics or indicators (e.g., customer service level, on-time delivery, costs, etc.)

Basic problems in decision-making include the following:

- optimality
- multiple objectives
- risk and uncertainty, and
- complexity

An optimal decision is the best one. Optimal decisions are very "fragile" and presume certain problem dimensionality, fullness and certainty of the model. Optimal solutions are usually very sensitive to deviations. Moreover, the decision making process is actually tightly interconnected with dynamics and should be considered as an adaptive tuning process and not as a "one-way" optimization process.

Consider an example: A typical optimization problem is the determination of optimal order quantity for some purchased items. This optimization process is

based on the reduction of ordering and inventory holding costs. If so, the calculated order quantity is optimal only for the purchasing department. At the same time, this problem is tightly interconnected with transportation planning and customer service level improvements. Therefore, the real problem situation, which exists, is integrated inventory optimization.

The problems of applying optimization-based decision-making are interrelated with complexity, uncertainty and multiple objectives. A particular feature of optimal decisions is *multi-objective* decision making by managers with their own preferences that, in turn, are always changing. Hence, it becomes impossible to build any general selection function for multi-criteria decision-making. Finding optimal solutions is possible, but can be very time-consuming. However, these optimal solutions can be used for benchmarking estimations of the quality of solutions obtained by heuristics or simulation models (see further in this Chapter).

Multiple objectives are conflicting in the sense of competing for common resources to achieve variously different performance objectives (financial, functional, environmental, etc.). A multi-criteria decision making strategy employs *trade-off* analysis techniques to identify compromise designs for which the competing criteria are mutually satisfied in a Pareto-optimal sense. For more detailed information on decision-making theory, we refer to the studies on operations research, decision theory, and quantitative analysis in management, e.g., Taha (2009), Render et al. (2012), Dolgui and Proth (2010), Yalaoui et al. (2012).

4.1.2 Models and Modelling

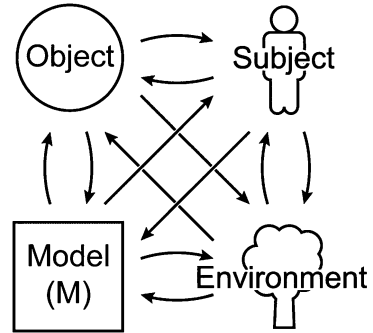
The concept of a model is widely applicable in natural human languages and is a general scientific term. It is characterized by polysemy, that is, widely expressed and reflecting different meanings of this concept depending on the applications and contexts. At present, there are several hundred definitions of the concept of a model and modelling. In summoning up different definitions, the following views of models and modelling can be presented.

A model is:

- a system whose investigation is a tool for obtaining information about another system;
- a method of knowledge existence; and
- a multiple system map of the original object that, together with absolutely true content, contains conditionally true and false content, which reveals itself in the process of its creation and practical use.

Modelling is one of the stages of cognitive activity of a subject, involving the development (choice) of a model, conducting investigations with its help, obtaining and analysing the results, the production of recommendations, and the estimation of the quality of the model itself as applied to the solved problem and taking into account specific conditions (Fig. 4.1).

Fig. 4.1 Modelling stakeholders



Because of the *finiteness* of the designed (applied) model (a limited number of elements and relations that describe objects belonging to an infinitely diverse reality) and the *limited* resources (temporal, financial and material) supplied for modelling, the model always reflects the original object in a simplified and approximate manner. However, the human experience testifies that these specific features of a model are admissible and do not oppose the solution of problems that are faced by subjects.

In the course of modelling, it is advisable to distinguish the following basic elements and relations: *first*, a subject or subjects, an original object, the model object and an environment in which the modelling is performed; and, *second*, binary relations between the listed elements. Subjects of modelling mean the following classes of social subjects: decision makers, persons who substantiate the decisions, experts, persons who use the models and persons who design the models.

It is worth noting that one of the main specific features of original objects (real or abstract) is their exceptional complexity, which reveals itself in the form of structural complexity, complexity of functioning, complexity of the choice of behaviour and complexity of development. In order to describe such objects we should use several models rather than a unique model. In other words, we should perform system modelling (a polymodel description of the application domain).

Another specific feature of the tools of abstract modelling consists of considerable intensification of works in the automation of this process and, first, the phase connected with the design of a computer model. Moreover, within the framework of new IT based on the concepts of knowledge bases, the concept of a “model” has considerably extended the limits of its application – from the field of passive informational resources to the field of *active* ones. Under these conditions, algorithms that are elements of procedural knowledge turn into operating environments that provide the solution to problems with a subject in the language of models.

The main properties of good models are the following:

- *Adequacy* (from Latin *adaequatus*, which means equated, completely suitable, or comparable). The model should possess the specified property relative to certain aspects of the original object.

- *Simplicity* and *optimality* of the model. The property of adequacy is directly associated with the properties of simplicity and optimality. Indeed, sometimes, to achieve the required degree of adequacy, we should essentially complicate the model. On the other hand, if we can choose different models that have approximately the same adequacy, it is advisable to use the simplest model.
- The *flexibility (adaptability)* of models assumes that parameters and structures that can vary in given ranges are introduced into the composition of models in order to achieve the goals of modelling.
- *Universality* and *task orientation* of models. It is advisable to design models specialized relative to an admissible class of modelled objects and universal with respect to a list of supported functions.

Among other properties of models, we should distinguish reliability, unification, openness and accessibility, intelligence, the efficiency of computer implementation, complexity, identifiability, stability, sensibility, observability of models, their invariance, self-organization and self-learning. Overall, each variant of implementation of the system modelling techniques is characterized by its own time consumption, the expenditure of resources and the results.

Finally, let us provide a general classification of different kinds of models. There are different options for classifying models. The first and most common option is to use the morphologic analysis and to distinguish two or three possible states for each feature. An example of such a classification is shown in Table 4.1.

4.1.3 Model-Based Decision-Making

With each decision, managers use both quantitative and qualitative models. Quantitative analysis is a scientific approach to managerial decision-making in which raw data are processed and manipulated to produce meaningful information. Consider an example (Ivanov et al. 2017).

Example “Re-designing the Material Flow in a Global Manufacturing Network”

Problem Description

Consider an enterprise that produces systems for energy transmission and has two locations: factory A is located in Europe and factory B is located in China. Both factories have deep manufacturing penetration; in other words, they are able to produce almost all the components and modules needed for the final product assembly. Both factories can assemble the same final products from the same components, known as shared components. The final assembly always takes place in the country where the customer builds its energy system. It should be analysed to

Table 4.1 Morphological model classification (Ivanov and Sokolov 2010)

Classification feature	Kinds of mathematical models		
	I	II	III
Scientific basis and building logic	Axiomatic	Empirical	Semi-empirical
	Hypothesis deductive (phenomenon logic)	Deductive–asymptotic	Inductive
	Deductive	Inductive	Deductive–inductive
Exactness	Analytical	Simulation	Analytical–simulation
Data and scope	Qualitative	Quantitative	Hybrid
Main model’s function	Descriptive	Predictive	Hybrid
Model selection alternatives	Satisfaction	Optimization	Non-alternative
Self-learning and self-organization	Self-learning	Self-organizing	Strictly predetermined
Time	Static	Kinematic	Dynamic
	Continuous	Discrete	Hybrid
Certainty	Deterministic	Stochastic	Uncertainty

see whether the production of the shared components can be distributed within the network so that total network costs are minimized.

Model Development

Each manager applies to each decision both quantitative and qualitative methods. From the mathematical point of view, the problem can be represented as a number of origin points with some capacities and destination points with some demand. The production volumes should be delivered to the customers in such a way that total costs are minimized. This is a well-known problem in operations research, namely the transportation problem. At the same time, the problem also comprises costs and risks, which cannot be quantified within an optimization model, and therefore additional qualitative analysis will be needed.

Input Data

At the first stage, four options for process design have been formulated:

1. Local manufacturing at A and B
2. Manufacturing at A for A and B
3. Manufacturing at B for A and B
4. Mixed manufacturing at A and B for A and B

For the development of the mathematical model, the following data is needed:

- origin points
- destination points
- production capacity at the origin points A_i
- demand at the destination points B_j
- costs for production and transportation of a product unit from A_i to B_j

Solution Development

A particular feature of the problem considered is that both the origin and destination points are actually identical. The model has then the standard format of the transportation problem and can be solved with the help of Excel Solver. Final decisions should be taken based on the analysis of both quantitative optimization results and managerial qualitative analysis.

Results Implementation

From the cost efficiency point of view, option 2 could be selected. However, some crucial risks exist. First, single sourcing strategy is very risky since production and delivery shortages can occur. Second, if manufacturing in Germany should be relaunched, implementation costs would be very high.

The model-based decision-making process comprises therefore the following steps as shown in Fig. 4.2.

We can observe that a *real management problem* is the initial point of the decision-making process. An example can be a facility location problem where we are given demand in some markets, possible locations and capacities of new facilities, fixed costs for having a facility in the supply chain, and transportation costs from each location to each market. The decision questions are where to locate the facilities and which quantities should be shipped from the facilities to the markets.

Next step is to transform the real problem into the *mathematical model*. For this transformation, we need to reduce the *complexity* of reality. This inevitably results in the simplification of reality. For example, we would assume deterministic capacity in our facility location model instead of considering fluctuations in demand.

We do this simplification in order to represent the management problem in the mathematical model in such a way that this model can be solved with the help of existing *algorithms* in a reasonable time. In our example, we formulate the facility location problem as a mixed-integer linear programming model that can be solved with the help of simplex and branch & bound algorithms.

For implementation, *software* is needed. Small instances can be solved with the help of Excel solver, but for real data, professional optimization solvers such as

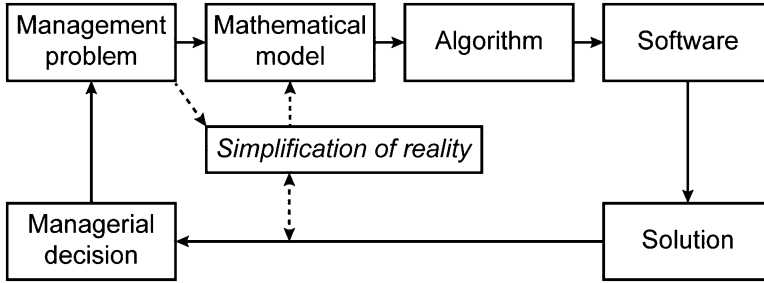


Fig. 4.2 Model-based decision-making process (Ivanov et al. 2017)

CPLEX, Lindo, AMPL, Marlab, GAMS, Gurobi, XPRESS and simulation software such as AnyLogic, anyLogistix, ARENA, LLamasoft Supply Chain Guru and many other exist. Software will calculate the *solution*. In our example, it would be the solution comprising the suggestions on where to open the facility locations and which product quantities should be shipped from each opened location to each of the markets so that total production and logistics costs are minimal.

Software calculated this solution. The most important question now is as follows: is this solution automatically our *decision*? NO! This is a solution to the mathematical problem. Now it is the stage where management expertise is needed to transfer this mathematical solution into the managerial decisions. First, simplifications of reality should be reviewed. Second, so called *soft facts* such as risks, flexibility, etc. should be included in the analysis. That is why we prefer talking about *decision-support quantitative methods*.

4.1.4 Quantitative Models and Operations Research

Quantitative models for supply chain management can be divided into three primary approaches. These are optimization, simulation and heuristics. Hybrid models (e.g., optimization-based simulation models) also exist. *Optimization* is an analysis method that determines the best possible option to solve a particular operations or supply chain problem. Optimization has been a very visible and influential topic in the field of supply chain management. The drawback of using optimization is difficulty in developing a model that is sufficient detailed and accurate in representing complexity and uncertainty of supply chain management, while keeping the model simple enough to be solved.

Simulation is imitating the behaviour of one system with another. By making changes to the simulated supply chain, one expects to gain understanding of the dynamics of the physical supply chain. Simulation is an ideal tool to further analyse the performance of a proposed design derived from an optimization model.

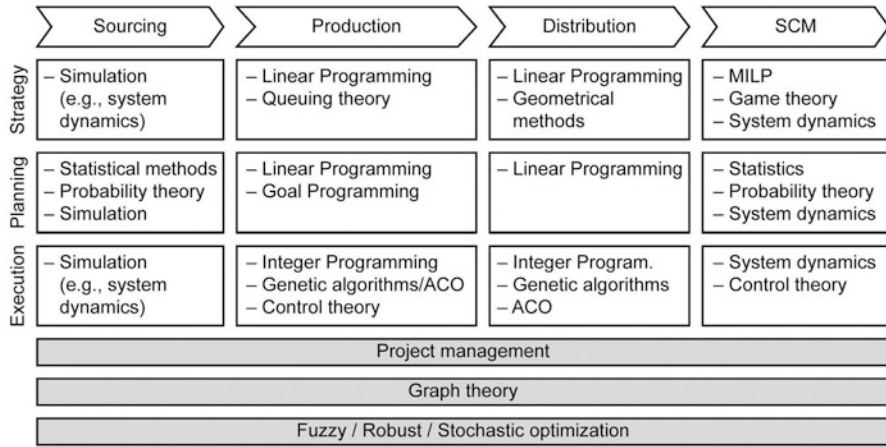


Fig. 4.3 Operations research methods for supply chain management (Ivanov et al. 2017)

Heuristics are intelligent rules that often lead to good, but not necessarily the best, solutions. Heuristic approaches typically are easier to implement and require fewer data. However, the quality of the solution is usually unknown. An option to estimate the quality of heuristic algorithms may be the usage of optimization as a tool for “ideal” solutions to problems.

Operations Research is the application of advanced analytical methods to help make better decisions (INFORMS definition). Operations Research deals with problems that may be described using mathematical models to find optimal or good solutions. Basically, Operations Research methods support the finding of solutions to *achieve the desirable goal(s) with limited resources*. An overview of Operations Research -based methods is presented in Fig. 4.3. Basic Operations Research methods and their application to supply chain management include but are not limited to:

- Linear programming (production planning; revenue management)
- Integer programming/Combinatorial Optimization (scheduling, routing)
- Mixed integer linear programming (supply chain design)
- Dynamic programming/Graph Theory (dynamic lot-sizing/supply chain contracting)
- Network theory (project management)
- Queuing theory (waiting lines: call centres, hotline services, process design, entertainment parks, services)
- Simulation (supply chain design, bullwhip-effect, etc.)
- Heuristics (genetic algorithms, ant colony optimization, application to scheduling and routing problems)
- Fuzzy/Robust/Stochastic optimization (data uncertainty)

The application of many of these methods to different supply chain management problems with structural dynamics and risk considerations will be considered in further chapters of this book.

4.2 Multi-disciplinary Nature of Quantitative Modelling Framework

Supply chain structural dynamics is characterized by uncertain interactions of the network elements, multiple objectives, uncertain environment, and complexity. Therefore, supply chain structural dynamics needs to be described by various models (static and dynamic, stochastic and deterministic, analytical and simulation, etc.), which are interconnected. Supply chains are also characterized by a set of interrelated structures.

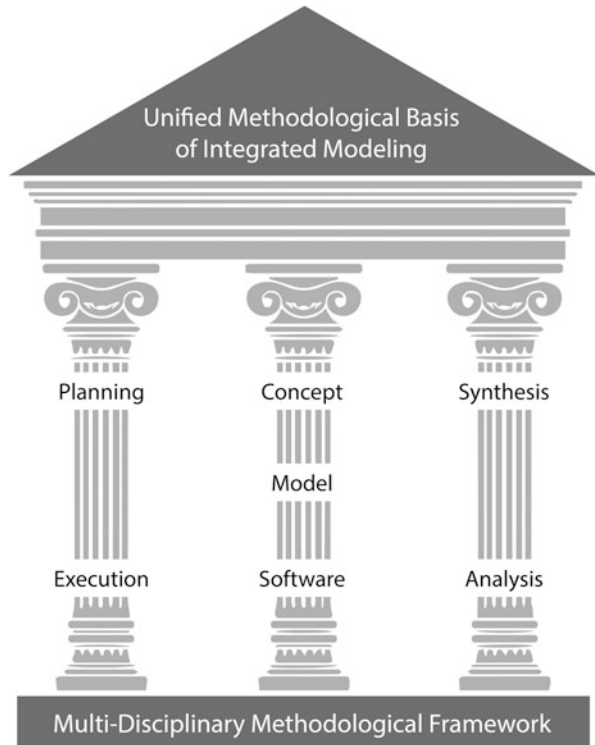
Furthermore, supply chain elements are active. Their activities are based on their own interests and goals. *Active* elements necessitate balancing supply chain partner interests, a large number of uncontrolled factors, and formalizing difficulties. Besides, supply chain execution is accomplished by permanent changes in the internal network properties and the environment. It requires supply chain adaptation to the current execution environment. So, reflections of supply chain configuration, planning and execution models are needed (Ivanov 2010). The other issue of supply chain modelling is the interlinking of conceptual and mathematical models in order to achieve adequate, scalable and representative models and providing application independence. Such a complex nature of supply chains requires a combined application of different disciplines and modelling approaches (Choi et al. 2016). Figure 4.4 depicts supply chain integrated modelling framework.

The main parts of the multi-disciplinary methodology are as follows: the general systems framework, the integrated modelling framework, and the computing framework (Fig. 4.5).

The general system framework defines conceptualized business models, meta-methodologies and a set of categories, definitions, specifications and performance indicators, which are developed during the integration of various theoretical frameworks. The integrated modelling framework defines the rules of the integrated multi-disciplinary mathematical model building. It proposes constructive methods and techniques of (1) how to combine various model classes and (2) how to interconnect partial supply chain problems. The computing framework integrates the building of mathematical models and algorithms, and their implementation as software.

Model integration as a key element of multi-disciplinary modelling framework is considered from four perspectives of system modelling: the integration of various modelling approaches and frameworks, the integration of planning and execution models, the integration of decision-making levels, and the implementation of

Fig. 4.4 Supply chain integrated modelling (Based on Ivanov 2009)



integration throughout: “conceptual model $\rightarrow$ mathematical model $\rightarrow$ computation” (see Figs. 4.6 and 4.7).

Supply chain strategy, design, planning and operations are interlinked with regards to constructing ideal supply chain states as well as to reconfiguring supply chains in relation to a current execution environment at strategic, tactical, and operational levels. The large variety of supply chain management issues can be classified into the subclasses of supply chain analysis and synthesis. The models of supply chain analysis can be divided into supply chain design analysis as well as supply chain operative monitoring (see Fig. 4.8).

The models of supply chain synthesis are composed of supply chain configuration and reconfiguration models. Most supply chain problems are cross-linked (i.e. models of supply chain monitoring and reconfiguration, static and dynamic models of the supply chain (re)configuration, supply chain synthesis and analysis models). Conceptual, mathematical and information models are also interconnected with each other.

The supply chains need to be configured according to project goals and reconfigured in dynamics according to the current execution environment. More typically, questions are centred on rationalizing supply chains in response to permanent changes in the supply chain itself and its environment. The general

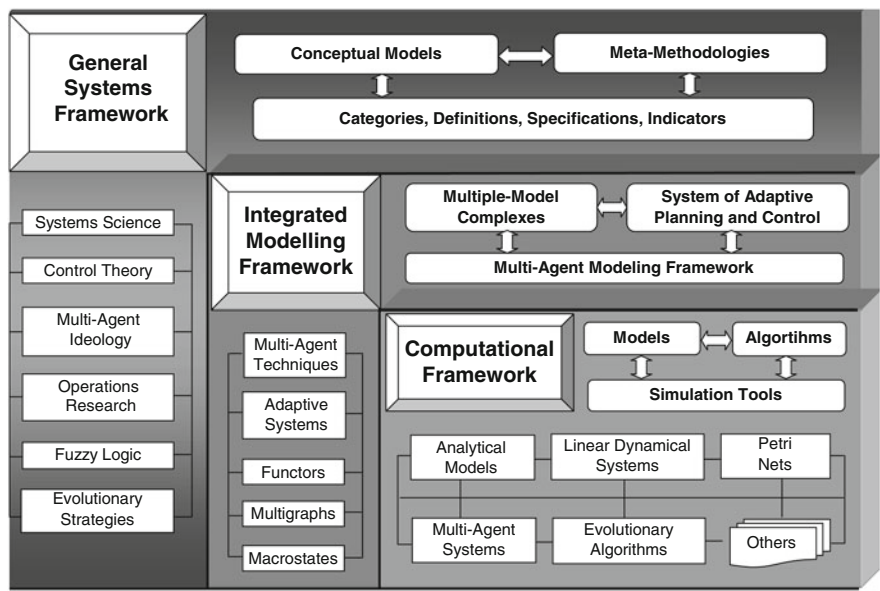
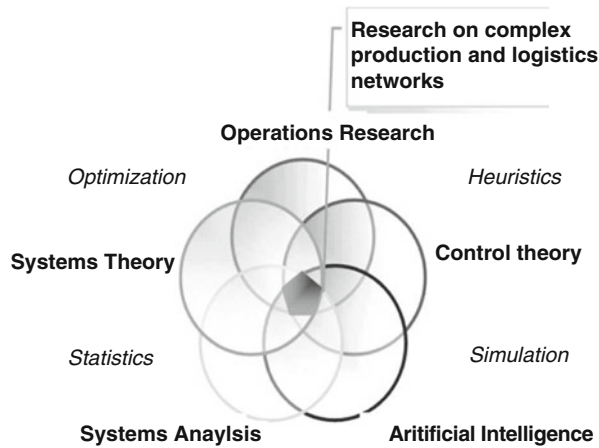


Fig. 4.5 Integrated modelling “concept-model-computation” (Ivanov 2009)

Fig. 4.6 Mathematical integration view



modelling structure of the supply chain dynamical structural–functional synthesis and reconfiguration is shown in Fig. 4.9.

Let us consider some examples. Transportation and inventory are primary components of the order fulfilment process in terms of cost and service levels. Therefore, companies must consider the important interrelationships among transportation, inventory and customer service in determining their policies. The suppliers’ selection is linked not only to their capacities, costs, etc. but also to their collaboration abilities. Therefore, coordination between the various players in the

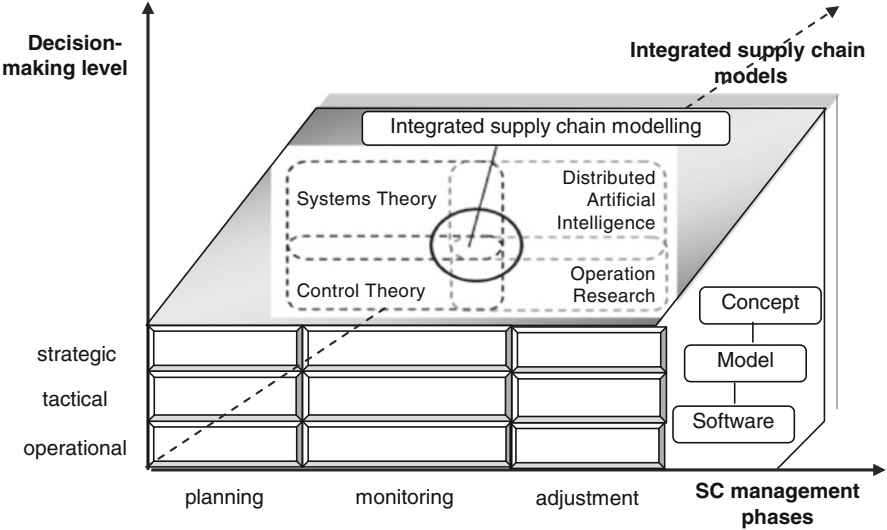


Fig. 4.7 Decision-making integration view

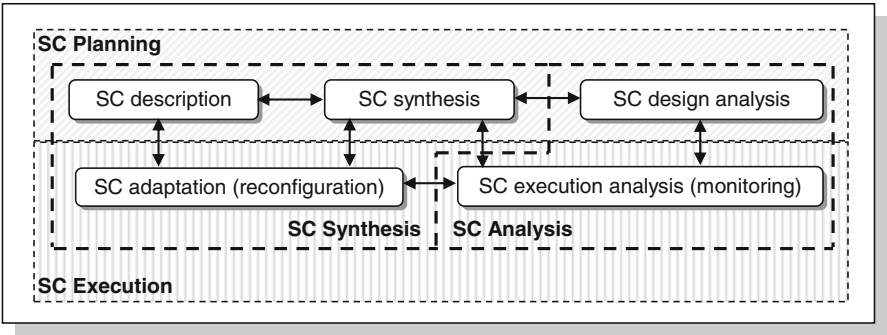


Fig. 4.8 Complex of conceptualized models for the problem of the supply chain dynamical structural-functional synthesis and reconfiguration (Adopted with changes from Ivanov 2010)

chain is the key to its effective management. Pricing and inventory decisions as well as product, distribution and production decisions are also matched together.

Let us consider the main steps of this schema referring also to the main phases of the supply chain management in Figs. 9.5 and 9.6. The modelling starts with the static graph-theoretical network description. The supply chain can be described graph-theoretically as a directed graph – a digraph. Then the elements of the organizational graph (enterprises) are described as active agents in terms of multi-agent theory. So the model of enterprise interactions can be constructed. In this stage, we combine graph-theoretical modelling with active agents to describe active elements of the graph as well as to implement modelling dynamics of the supply chain objects' collaboration.

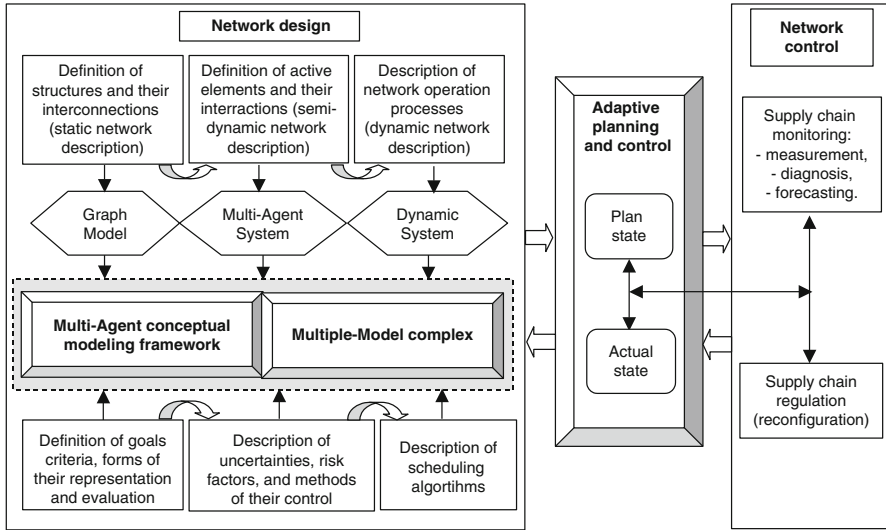


Fig. 4.9 The general modelling schema of the supply chain dynamical structural-functional synthesis and reconfiguration (Ivanov et al. 2007)

The goal of the coordinator consists of project description and structuring according to the proper level of decomposition. Any project can be presented as several consecutive and/or parallel operations. In complex projects, different operations have different degrees of importance to the final result. That is why the importance level of each operation must be taken into account. When a coordinator is in charge of several projects, there may be situations where the same competency is needed for different projects at the same time. These projects should not be considered independently because they compete for the same resources. In order to analyse such “linked” projects, we propose to present them as a joined structure scheme that we call a technological network. The model of the technological network is an oriented graph. Its heads are considered competencies that are necessary for project realization, and its edges serve to show the logical sequence of operations. The weights of each head reflect the volume of the competency that is needed for the project’s performance (e.g. the total working time to execute a concrete technological operation on a concrete machine). Finally, at the end of this step, the coordinator obtains properly structured projects that are considered as a technological network. The next step is dynamic network description. In this stage, a set of interlinked dynamic models is formed to link the “ideal” planning results to the supply chain execution programmes under uncertainty.

The models of supply chain execution are comprised of supply chain monitoring and supply chain regulation (reconfiguration) models. Supply chain monitoring is based on the monitoring of the supply chain macro-structural macro-states (cf. - Chap. 1). The monitoring plan execution consists of determining diagnostics moments (critical control points), when the analysis of the planned and factual

parameters of supply chain execution (demand, inventories, jobs' starting and ending, and stability) is carried out. A particular feature of supply chain monitoring in terms of macro-states is that, at each monitoring stage, the control parameters are extracted from the parameter vector of the dynamic alternative multi-graph. The mathematical description of the dynamic alternative multi-graph has been considered in Chap. 1, see Eq. (1.1). The extracting rules depend on management goals at the stage monitored. This makes it possible to consider all of the supply chain execution parameters described in the dynamic alternative multi-graph and to extract the necessary control parameters in the current execution situation.

Supply chain reconfiguration (real-time re-planning) is comprised of deviations analysis, the elaboration of compensating control actions and the construction of a new plan and production of appropriate correcting actions for the transition from the actual supply chain state trajectory to the planned one at a given time interval or by the final time. The model of supply chain reconfiguration is interconnected to the planning model. It is also based on the dynamical alternative multi-graph. While selecting a new supply chain, it is also essential to take into account a number of specific requirements (preferences of the supply chain focal enterprise or 4PL provider and suppliers at different supply chain levels). The essence of decision making about supply chain reconfiguration, that is to say about a supply chain plan transition from a current state to a desired state, is to ensure that the agents' interests and the interests of a supply chain coordinator comply with each other.

4.3 Modelling Paradigms

4.3.1 *Mathematical Optimization*

Optimization is an analysis method that determines the best possible method of designing a particular supply chain. Optimization methods have been a very visible and influential topic in the field of supply chain management (Yalaoui et al. 2012; Martel and Klibi 2016). The main advantage of the optimization approach is the idea of *optimality* and striving for the best solution. However, the optimal approach should be very carefully considered. The problems of applying optimization-based decision-making are tightly interrelated with complexity, uncertainty and multiple objectives. Optimal approaches are very "fragile" and presume certain problem dimensionality, fullness and certainty of the model. Besides, optimal solutions are usually very sensitive to deviations. Moreover, the decision making is actually tightly interconnected with dynamics and should be considered as an adaptive tuning process. A particular feature of complexity in supply chains is multi-criteria decision making by managers with their own preferences that, in turn, are always changing. Hence, it becomes impossible to build any general selection function for multi-criteria decision-making.

The drawback of using optimization is the level of difficulty in developing a model that is sufficiently detailed and accurate in representing complexity and uncertainty of supply chain management while keeping the model simple enough to be solved. Furthermore, most of the models in this category are deterministic and static. Additionally, those that consider stochastic elements are very restrictive in nature.

Indeed, with regards to supply chains as complex systems, optimization can be realistically considered as the direction for best solutions and the ideology of decision-making. Finding optimal solutions is possible, but it can be very time-consuming. However, these optimal solutions can be used for benchmarking to estimate the quality of solutions obtained by heuristics or simulation models. Unless mitigating circumstances exist, optimization is the preferred approach for supply chain management. However, in reality, only a few partial supply chain management problems (mostly of a strategic nature) may be correctly addressed by optimization.

4.3.2 *Simulation*

Equation systems that are good at expressing static dependencies between parameters and variables typically are restrictive in describing systems with dynamic behaviour. It's why another modelling technology – *simulation modelling* – to analyse dynamic systems is applied. *Simulation* involves imitating the behaviour of one system with another. By making changes to the simulated supply chain, one expects to gain understanding of the dynamics of the physical supply chain.

Three major simulation approaches have been identified (Tako and Robinson 2012; Borshev 2013):

- discrete-event simulation
- system dynamics
- agent-based simulation

Each method serves a specific range of abstraction levels. System dynamics assumes very high abstraction, and it's typically used for strategic modelling. Agent based models can vary from very detailed models where agents represent physical objects to highly abstract models where agents represent competing companies or governments. Discrete event modelling supports medium and medium-low abstraction.

Supply chain simulation utilizes three classes of *software tools*:

- all-purpose discrete event simulation tools;
- specific supply chain simulation software; and
- supply chain management software with simulation functionality.

Two classes of *dynamic models*, namely continuous and discrete models, are widely used to depict process sequences in flow systems. Continuous models are

based on differential equations and are most frequently applied as system dynamics models to reproduce manufacturing and logistics processes (Sterman 2000). System dynamics models are relatively rarely developed since planners often find the models in this class too abstract or are unable to generate them. Since these models normally relate relatively rough to real problems and very abstractly, they are hereafter referred to as macroscopic models (Tolujev 2008). Operative planning routinely applies microscopic discrete-event models. The principles and tools of discrete-event simulation are utilized to implement discrete models. Since workstations, technical resources, carriers and units of goods are represented as individual objects in most cases, event-oriented models may also be referred to as microscopic models.

4.3.3 Optimization-Based Simulation

One promising area in model-based decision-making is the study of combining simulation methods with optimization methods in an iterative way that is referred to as an *optimization-based simulation* (Almeder et al. 2009; Gao and Chen 2017). For example, Meisel and Bierwirth (2014) utilized simulation and optimization methods to analyse the performance of a make-to-order strategy in the presence of uncertainties. Ivanov et al. (2016) applied a hybrid optimization-based simulation approach to analysing supply chain disruptions and recovery strategies.

In Table 4.2, advantages and limitation of optimization are summarized.

Simulation methods do not guarantee optimality and development of simulation model can be a complex task even with the use of special software. However, simulation provides a number of advantages that compensate for optimization limitations. In particular, in simulation models it has become possible to

- analyse systems and find solutions where methods such as analytic calculations and mathematical programming fail
- measure values and track entities within the level of abstraction
- add measurements and statistical analysis any time
- manipulate and animate the system behaviour in real time

Therefore, simulation is an ideal tool for further analysing the performance of a proposed design derived from an optimization model (Ivanov 2017).

Table 4.2 Advantages and limitations of optimization

Advantages	Possible limitations
Optimal solution	Dimensionality and complexity of real problems
Methodical basics	Dynamics and uncertainty of system and model evolution
Easy accessibility	Poor flexibility
	Linearity and discreteness

4.3.4 Control Theory

Control theory (control theory) as a base for studying multi-stage, multi-period dynamic systems is an interesting research avenue to extend existing results while taking into account the intrinsic peculiarities of modern supply chains. Control theory contains a rigor quantitative basis for planning optimal control policies including differential games and stochastic systems, stability of controlled processes and non-linear systems, controllability and observability, and adaptation (Perea et al. 2000; Sethi and Thompson 2000; Disney et al. 2006; Sarimveis et al. 2008; Ivanov et al. 2012; Fu et al. 2015).

These tools can be applied for a wide range of systems, from discrete linear to stochastic non-linear systems with both stable and dynamically changing structures. Control theory can also be applied to analysis of equilibriums of resource consumption and system output. Applications of control theory, simulation and systems science to supply chain dynamics are multi-faceted. Disney et al. (2006), Sarimveis et al. (2008) and Ivanov et al. (2012) underline the resemblance of supply chains to engineering dynamic systems.

Control theory is a multi-disciplinary scientific discipline that contains powerful conceptual and constructive tools to conduct research on the dynamic problems of flexible (re)distribution of a variable set of jobs to a variable set of resources.

Control theory is tightly interconnected with cybernetics. Wiener (1948) proposed summing up the whole area of regulation and communication theory under the term “cybernetics”: “We have decided to call the entire field of control and communication theory, whether in the machine or in the animal, by the name Cybernetics”.

The renovation of cybernetics has two sources. The first source lies in the attempts to revise the methodological backgrounds of cybernetics. Maruyama (1963) paid attention to the systems in which mutual causal effects are deviation-amplifying. Economic, social, and biological examples were considered.

In contrast to Wiener’s cybernetics with deviation-counteracting systems, the studies of deviation-amplifying mutual causal relationships were called “the second cybernetics”. Von Foester (1974) defined “the second-order cybernetics” with awareness that an observer is an element of the system. The studies considered processes resulting in an increase in biological and social complexity. Stafford Bear, in his work since 1974, has emphasized that investigation into complexity problems should evolve Ashby’s law of requisite variety (Ashby 1956).

Unfortunately, the logically relevant chain of fundamental notions of cybernetics – control – informational processes – universal transformer of information (computer, cybernetic machine) was split. An expansion of computer technologies caused the illusion of their ability to solve any problem. The imperfection of these technologies has already caused catastrophes that allowed scientists to proclaim the establishment of a “risk society” rather than an “informational” one. This inspires a renewed interest in the theoretical background of control problems.

Within control theory, different control approaches exist, i.e. optimal control, adaptive control, and intelligent control. One of the most popular techniques of optimal control is the *model predictive control*. Model predictive control has been a preferred algorithm for robust, multi-variable control that has been widely used in process industries. The popularity of Model predictive control stems from the relative ease with which it can be understood, and its ability to handle input and output constraints.

Model predictive control is a control strategy based upon the explicit use of a process model to predict the process output (performance) over a long period of time (Camacho and Bordons 2004). The model attempts to predict the control variables for a set of time periods. Predicted control variables depend on disturbance forecasts (i.e. demand, prices and interest rates) and also on a set of given parameters that are referred to in control literature as control inputs.

In Model predictive control, a system model and current and historical measurements of the process are used to predict system behaviour at future time instants. A control-relevant objective function is then optimized to calculate a sequence of future control moves that must satisfy the system constraints. As a control-oriented framework, a model predictive control-based planning scheme has the advantage that it can be fine-tuned to provide acceptable performance in the presence of significant uncertainty, forecast error, and constraints on inventory levels, production, and shipping capacity. However, the “optimal control” structure in model predictive control is only a means to achieve such a result as it does not optimize a true performance index of the closed-loop control system.

Adaptive control is a control strategy with some form of recursive system identification. Usually, a parametric adaptive control is considered (Sasthy and Bodson 1994). Research in AC has a long and vigorous history. Kalman (1960) developed the concept of a general self-tuning (adjusting) controller with explicit identification of the parameters of a linear, single-input, single-output plant and proposed to use these parameters’ estimation to update an optimal linear quadratic controller. In the 1960–70s, due to the establishment of Lyapunov’s stability and proving convergence in adaptive control systems, stochastic control made giant strides understanding dynamic programming due to Bellmann and others (Bellmann 1972). In the 1980s, adaptive schemes for different applied domains appeared. However, the adaptive control approach has not found a wide application in the supply chain management domain. The main cause of this is that adaptive control techniques are intended for technical systems with an automatic controller and automatic reactions of milliseconds. This is not the case in supply chains. However, the main principles of adaptive control (not the formal techniques) can enrich the control framework for supply chain management that will be shown later in this study.

Interest in Control theory is of great interest to researchers and practitioners. Control theory is favourable in cases of many dynamically changing control parameters, obtaining analytical solutions or properties, and in investigating different mutual impacts of supply chain planning and control parameters (e.g., demands, resource and channel capacities, lead-time, lot-sizes, and inventories) in the supply

chain tactical and operative performance (i.e., service level and costs). In some cases (e.g., if there are many changes, many stages, and many periods), it is convenient to transit from a discrete problem statement to continuous solution procedure, and then represent the result again in discrete terms due to particular accuracy of continuous time models.

Employment of control theory can be seen as the next crucial step in the development of supply chain management theory to reflect real-time dynamics and dynamic optimization of supply chain structures and processes as well as explore robustness, stability, and adaptability in real-time mode taking into account non-linearity, non-stationarity and uncertainty in supply chains.

Dynamics in supply chains can be referred to both as the dynamics of a process under optimization (dynamics of the transition from an input to an output state) and the real-time dynamics regarding the feedback-loop consideration and adaptation in accordance with an actual execution environment. Employment of control theory can be favourable for both supply chain synthesis and analysis stages.

Optimal control approaches can be efficiently used for optimal design, planning and scheduling of complex multi-stage, multi-period and multi-commodity supply chains. However, an important precondition is the existence of centralized information for the whole network and relevant parameters. In practice, it is rather rare that firms really share complete data on inventories, demands, and capacities. Therefore, optimal control can be efficiently applied only for centralized information strategies.

Such cases are very common in supply chains, e.g., with original equipment manufacturers, by applying the CPFR (collaborative planning, forecasting and replenishment) coordination strategy or in supply chains which are managed by logistics service providers. However, even if decentralization and contradictory goals of enterprises in a supply chain do not allow for the implementation of optimal program control, optimal solutions under assumptions of full information sharing may be considered as an orientation for the estimation of any decentralized plans and schedules that can be found, e.g., with the help of agents.

Linear control theory can be efficiently applied to multi-echelon inventory control problems with full information sharing, e.g. vendor-managed inventory. In addition, information delays can be efficiently investigated with linear control theory. The bullwhip-effect and stability of supply chains can be approached in the frequency domain of the linear control theory, though purely under the assumption of relatively small dimensionality. For the stage of execution control (again, under the assumption of immediate and full information sharing), model predictive control methods can also be applied.

The following research issues can be indicated:

- *Issue 1 – Synthesis models – complexity and content of planning models and their interconnection with control models.* Supply chains are increasingly more and more complex. It is becoming ever more difficult to represent the progressively more complex supply chain management problems within only one model taking into account dynamic supply chain processes.

Table 4.3 Applications of modern control theory to supply chain management (Ivanov et al. 2012)

The main results of modern control theory	Implementations for supply chain control
Criteria for existence of a solution	Model verification for supply chain control
Criteria for controllability and attainability	Control processes verification for a given time interval/ determination of the constraints on supply chain goals
Criteria for uniqueness of optimal program control	Analysis of possibility to obtain an optimal plan
Necessary and sufficient conditions of optimality	Preliminary analysis of optimal program controls; generation of basic supply chain planning algorithms
The program control and feedback control	Supply chain planning, scheduling and execution control models on united methodological basis
Criteria for stability and resilience	Evaluation of supply chain robustness, stability and resilience for environmental impacts and alteration of input data

- *Issue 2 – Analysis models – executability, robustness, stability and adaptation.* Planned performance success can be thwarted by perturbations. This forces research on re-planning and control to make supply chains reliable and flexible enough to be able to adapt when disturbed and remain stable and robust.

With regard to the abovementioned research gaps, employing control theory methods is becoming timely and crucial. Supply chains *resemble control systems as multi-stage dynamic flow of materials with information feedback*. Control theory contains a rigorous quantitative basis for planning multi-stage dynamic systems. Control theory tools can be applied to a wide range of systems, from discrete linear to stochastic non-linear systems with both stable and dynamically changing structures. In Table 4.3, possible applications of modern control theory results to supply chain management are summarized.

Control theory takes into account dynamics, real dimensions, non-linearity and non-stationary of supply chain processes. However, *although supply chains resemble control systems, they have some peculiarities which do not allow direct application of control theory methods*. Classical control theory leads us to the fields of automatic control. In supply chains, the controllers are human beings.

Supply chain fine tuning occurs not within milliseconds but with a time delay. Supply chain managers consciously tend to take risks. In light of multi-criteria problems, decisions in supply chains are typically made based on individual psychological risk perceptions and preferences. Hence, interactive tools for multi-criteria decision-making are needed. Decision-making in supply chains is of a discrete nature. In technical control systems, it is assumed that control is selected continuously. Besides, in optimal control theory, differential equations express the process dynamics of the systems' behaviour in the input-output context. These non-linear mathematics in a supply chain management context are a promising research area (Spiegler et al. 2016).

We conclude that one of the fascinating features of control theory is the extraordinarily wide range of possible applications. Control theory is vital in unlocking many system improvement opportunities. The *first* strong contribution of control theory to operations and supply chain management regarding the dynamics is the interpretation of planning and execution processes not as isolated domains but as an adaptive process. *Second*, an advantage of control theory is the possibility to solve problems with non-stationary and non-linear processes due to the independency of time variables. Continuous dynamic models allow us to establish and optimize supply chain performance indicators in dynamics that are difficult to express within static and discrete time models. *Third*, the possibility of covering supply chain dynamics at the process level and the changes in the supply chain and the environment are also strong contributions of control theory. *Fourth*, control theory allows for the consideration of goal-oriented formation of supply chain structures and the solution of problems in this system as a whole. *Fifth*, in using control theory, important categories of supply chain analysis such as stability, robustness and adaptability can be taken into consideration.

However, some peculiarities of supply chains as technical-organizational systems do not allow direct application of control theory methods. For this reason, a combined application of control theory, operations research, and artificial intelligence can be favourable. In addition, *ipso facto* that a supply chain plan and schedule can be formulated as optimal program control is a great advantage subject to further dynamics analysis that is a crucial application area of control theory to supply chain management. Even in this area, control theory can be applied to supply chain management to a greater extent and enlarge the scope of supply chain dynamics analyses that is currently rather limited.

4.3.5 Heuristics

Heuristics are intelligent rules that often lead to good, but not necessarily the best, solutions. Heuristic approaches typically are easier to implement and require less data. However, the quality of the solution is usually unknown. Unless there is a reason not to use optimization, heuristics are an inferior approach. In supply chain settings, nature-based heuristics such as genetic algorithms and Ant Colony Optimization are usually applied.

Heuristics (e.g. genetic algorithms) are usually applied instead of optimization because of computational complexity. They do not guarantee the optimal solution but allow a permissible result to be found within an acceptable period of time. The quality of this solution with regards to the potential optimum, however, remains unknown. Second, multiple objective problems are still a “bottleneck” of heuristics.

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Chapter 5

OR/MS Methods for Structural Dynamics in Supply Chain Risk Management

5.1 Literature Selection Principles

In this Chapter, we analyze state-of-the-art research streams on managing operational and disruption risks in supply chain design and planning. It structures and classifies existing research and practical applications of different quantitative methods subject to recently derived empirical frameworks. We identify gaps in current research and delineate future research avenues. The results of this literature analysis are twofold. Supply chain managers can observe which quantitative tools are available for different applications. On the other hand, from the point of view of operational research, limitations and future research needs can be identified for decision-supporting methods in supply chain risk management domains.

Supply chain design has been a visible and influential topic in the field of production, operations, and supply chain management (supply chain management) over the past two decades. Beginning with the seminal work of Geoffrion and Graves (1974) on multi-commodity distribution system design, many approaches have been proposed for the design of supply chains (supply chain) (Daskin 1995; Drezner 1995; Vidal and Goetschalckx 1997; Goetschalckx et al. 2002; Amiri 2006; Manzini and Bindi 2009; Melo et al. 2009; Georgiadis et al. 2011; Askin et al. 2014; Kılıç and Tuzkaya 2015).

Making decisions in supply chain design involves facility location planning, allocation of customers, and supplier selection (Melo et al. 2009; Chopra and Meindl 2012; Sawik 2013; Ivanov et al. 2017). In many cases, inventory, lead-time and demand fluctuations are integrated into these models (Sourirajan et al. 2009; Sadjady and Davoudpour 2012; Singh et al. 2012; Kumar and Tiwari 2013; Pan and Nagi; 2013; Askin et al. 2014).

These decisions can be extensively supported by methods of quantitative analysis, which typically compute optimal supply chain design structure based on several assumptions about demand, supply and transportation capacities. The

objective is to successfully meet customer needs while improving the efficiency of operations performance. The results of supply chain design are considered inputs to supply chain planning decisions: these include inventory management and control, contracting, distribution and transportation planning (Manzini and Bindi 2009; Ravindran et al. 2010; Costantino et al. 2012; Bowersox et al. 2013; Ivanov et al. 2014b).

In both supply chain design and supply chain planning, it is mandatory to account for uncertainty and risk in order to provide practically relevant problem statements and decision-oriented solutions. Recent literature suggests considering *recurrent* or *operational* risks and *disruptive* risks (Chopra et al. 2007). For example, the risks of demand and lead-time uncertainty are related to random uncertainty and business-as-usual situations. Such risks are also known as *recurrent* or *operational risks* (Kleindorfer and Saad 2005; Chopra et al. 2007; Acar et al. 2010; Georgiadis et al. 2011; Meisel and Bierwirth 2014; Ivanov et al. 2017) and are frequently considered in the framework of the *bullwhip-effect* (Ouyang and Li 2010). Supply chain managers have achieved significant improvements in managing supply chains and mitigating recurrent supply chain risks by improving coordinated planning and execution, e.g., vendor-managed inventory (VMI) or collaborative planning, forecasting and replenishment (CPFR) (Chopra and Sodhi 2014; Govindan 2015; Xu et al. 2015).

From 2000 to 2017, supply chain disruptions (e.g., because of both natural and man-made disasters, such as the earthquake on 11 March 2011 in Japan, the floods in Thailand also in 2011, the fire in the Phillips Semiconductor plant in New Mexico in 2000, etc.) occurred in greater frequency and intensity, and thus with greater consequences than previously (Chopra and Sodhi 2014; Simchi-Levi et al. 2014). Such *disruptive risks* represent a new challenge for supply chain managers who face the *ripple effect* subject to *structural disruptions* in the supply chain, unlike the *parametrical deviations* of the bullwhip effect (see Chap. 3).

Recent studies have extensively considered supply chain design and supply chain planning and taken disruption risks into account (e.g., Xia et al. 2004; Snyder and Daskin 2005; Xiao and Yu 2006; Wilson 2007; Cui et al. 2010; Baron et al. 2011; Chen et al. 2011; Peng et al. 2011; Kouvelis and Li 2012; Schmitt and Singh 2012; Baghalian et al. 2013; Li et al. 2013a; Lim et al. 2013; Qi 2013; Ivanov et al. 2013, 2014a; Sawik 2013; Paul et al. 2014). A number of remarkable state-of-the-art reviews and conceptual frameworks have been published in this area (Klibi et al. 2010; Lim et al. 2010; Qi et al. 2010; Blackhurst et al. 2011; Christopher et al. 2011; Klibi and Martel 2012; Simangunsong et al. 2012; Pettit et al. 2013; Tang et al. 2014; Ambulkar et al. 2015).

In the last decade, reasons for operational and disruption risks in supply chains have been extensively investigated. The qualitative analysis by Hallikas et al. (2004), Zsidisin et al. (2004), Hendricks and Singhal (2005), Kleindorfer and Saad (2005), Tomlin (2006), Craighead et al. (2007), Ritchie and Brindley (2007), Blackhurst et al. (2011), Bode et al. (2011), Chaudhuri et al. (2013), Chen et al. (2013), Pettit et al. (2013) and Ambulkar et al. (2015) revealed two basic approaches for hedging the supply chain against the negative impacts of

different disruptions – *proactive* and *reactive*. During the generation of a supply chain's design, the proactive approach creates certain protections and accounts for possible perturbations without recovery considerations (Klibi et al. 2010). The reactive approach aims to adjust supply chain processes and structures when unexpected events occur (Knemeyer et al. 2009).

The literature selection for this Chapter has been made on the basis of the following principles. The first principle is to achieve the objectives of this study. These objectives include:

- identifying causes of risk in supply chains in both qualitative and quantitative literature
- identifying measures for supply chain recovery in both qualitative and quantitative literature
- bridging causes and recovery measures for the development of contingency plans
- deriving commonalities/differences in qualitative and quantitative research on supply chain risks
- analyzing different methods for quantitative analysis of supply chain design and supply chain planning.

The second principle is to select literature with a high impact factor from leading scientific journals. The third principle is to present a state-of-the-art review on a broad, multidisciplinary basis. The fourth principle is to cover two groups of problem statements:

- risk consideration without recovery measures;
- risk consideration with recovery measures.

The fifth principle is to focus on the following quantitative methods:

- mixed-integer programming,
- stochastic programming and fuzzy/robust optimization,
- simulation and control theory,
- pricing and game theory.

The final, sixth, principle is to promote understanding of the supply chain as a multi-structural dynamic system (cf. Chap. 1).

We emphasize that this analysis does not pretend to be a full collection of the papers published on the selected topic, but rather aims to bridge scientific results and managerial needs in order to provide supply chain managers with an overview of current research trends in the area.

5.2 Mixed-Integer Programming

Mixed-integer programming with application to reliable supply chain design has been a broad research avenue over the past 10 years. More precisely, incapacitated, fixed charge location models and P -median problems have been the most studied. The reliable location model was first introduced by Snyder and Daskin (2005). The model aims at finding the optimal supply chain design with assignments of customers to locations with the objective of minimizing the sum of fixed and transportation costs in the supply chain. The study by Snyder and Daskin (2005) assumed equal estimations of probability failures for all the supply chain nodes and considered a case with 49 cities in US.

This model has been extended by Cui et al. (2010), who relaxed the assumption of homogenous failure probability. In addition, Cui et al. (2010) paid attention to the fact that total transportation costs in the supply chain should not increase after a disruption. Their model provides the solution without an increase in transportation costs for both normal and disruptive modes.

Since most of the resulting models became non-linear, mixed-integer programming, different linearization methods and heuristic solutions have been successfully developed, e.g., on the basis of continuum approximation. For medium-size problems, as documented in Li et al. (2013a), Lagrangian relaxation also facilitates the finding of optimal solutions within a reasonable time.

The next development of mixed-integer programming models concerns facility fortification. Lim et al. (2010) incorporated a totally reliable back-up supplier that can be used if a primary supplier is destroyed. The related costs are incorporated into the objective function, but the fortification budget remains incapacitated. Li et al. (2013a) extended this model by introducing limits on the fortification budget in a single-product case with eight distributors and up to 150 customers.

In addition, inventory considerations have been included. Chen et al. (2011) presented a joint inventory-location model under the risk of probabilistic facility disruptions. Benyoucef et al. (2013) considered supply chain design with unreliable suppliers. The objective was to minimize fixed location costs, inventory and safety stock costs at the distribution centers, and ordering costs and transportation costs across the network. The non-linear mixed-integer programming model was solved with the help of Lagrangian relaxation. Inventory management under supply chain disruption involves non-linear cost components. Therefore, heuristic solution methods are typically used. In addition, lead-time uncertainty constraints may be included (Mohebbi 2003; Acar et al. 2010).

Losada et al. (2012) used bilevel, mixed-integer programming to protect an incapacitated median type facility network against worst-case losses. How the length of time taken for a facility to recover affects system performance, as well as the possibility of multiple disruptions over time, is considered. Costantino et al. (2012) presented a hierarchical approach to strategic supply chain design, addressing supply planning and improving the agility of the manufacturing supply chain in terms of its ability to reconfigure to meet performance, and considering

supplier capacity constraints. The approach employs digraph modeling and integer linear programming for optimal supply chain design. The authors avoid stochastic models by aggregating deterministic product flows within the integer linear programming model.

The study by Lim et al. (2013) turned away from probability estimation issues and faced the trade-off that occurs between under- vs overestimation of disruption probabilities. This study provided evidence that underestimation of disruptions may have a significantly higher impact on total supply chain costs compared to overestimation. Such analysis has been performed on the basis of a stylized continuous location model.

Rafiei et al. (2013) developed a comprehensive model for a problem statement with multiple products and many periods. They considered the levels of inventory, back-ordering, available machine capacity and labor levels for each source, transportation capacity at each transshipment node and available warehouse space at each destination. The problem also addressed facility fortification by taking a back-up supplier with reserved capacity and a back-up transshipment node that satisfied demands at higher prices without disrupting the facility into account. The solution to the model is built on a priority-based genetic algorithm.

Ahmadi-Javid and Seddighi (2013) developed a solution to a location-routing problem for a supply chain where the production capacity of each producer–distributor varied randomly, and the vehicles involved in the distribution system were disrupted randomly. The model helps to determine the location, allocation and routing decisions that minimize the annual cost of location, routing and disruption. To solve the problem, an exact and heuristic algorithm are developed.

Gedik et al. (2014) modelled disruptions and train re-routing actions in a coal supply chain network, and assessed impacts of disruptions in terms of transportation and delay costs using a two-stage mixed-integer programming model. An “interdictor” chooses a limited number of elements to attack first on a given network, and then an “operator” dispatches trains through the residual network. The mixed-integer programming model explicitly incorporates the discrete unit flows of trains on the rail network with time-variant capacities. A K-th shortest path algorithm is used to enumerate all routes between points. The authors considered a real coal rail transportation network and generated scenarios to provide tactical and an operational level vulnerability assessment analysis with the incorporation of rerouting decisions, travel and delay cost analysis, and the frequency of interdictions of facilities for the dynamic rail system.

Hasani and Khosrojerdi (2016) developed a non-linear mixed-integer programming model and used it to model resilience strategies to mitigate the risk of correlated disruptions. The solution is implemented as a Taguchi-based memetic algorithm that incorporates a customized hybrid parallel adaptive large neighborhood search. The model was applied to a real-life case study of a global medical device manufacturer.

5.3 Stochastic Programming/Fuzzy and Robust Optimization

In a stochastic programming approach, the objective function contains the sum of the first-stage performance measure and expected second-stage performance. Stochastic programming models are scenario-based, and parameters are represented by a set of discrete scenarios with a given probability of occurrence.

In classical stochastic programming models (Tsiakis et al. 2001; Santoso et al. 2005; Goh et al. 2007), demand is considered an uncertain parameter. In robust stochastic programming models (Azaron et al. 2008), facility disruptions and capacity expansion costs are also considered uncertain. Schütz et al. (2009), Iakovou et al. (2010), and Baghalian et al. (2013) extended the existing models by considering demand-side and supply-side uncertainties simultaneously. Kılıç and Tuzkaya (2015) proposed a two-stage, stochastic mixed-integer programming method to model demand uncertainties in a multi-product, two-echelon, multi-mode and multi-period distribution network. The model provides support for decisions on facility location and transportation.

Benyoucef et al. (2013) considered a two-period supply chain design model in which selected suppliers are reliable in the first period and can fail in the second period. The corresponding facility location/supplier reliability problem is formulated as a non-linear stochastic programming problem. The authors used a Monte Carlo approach in combination with Lagrangian relaxation. Sawik (2013) developed a stochastic programming model to integrate supplier selection, order quantity allocation and customer order scheduling in the presence of supply chain disruption risks.

The study by Petrovic et al. (1998) was among the first papers on the application of fuzzy optimization to supply chain design with the uncertainty of demands and external supply. The objective was to determine the stock levels and order quantities to obtain an acceptable delivery performance at a reasonable total cost for the supply chain. Aliev et al. (2007) applied fuzzy mathematical programming with a fuzzy objective function solved by genetic algorithm. Like Petrovic et al. (1998), this study treated customer demand and production capacity as uncertainties. The objective was to provide a sound trade-off between maximization of profit and service level. Costantino et al. (2011) presented a fuzzy programming approach for the strategic design of distribution networks.

Ravindran et al. (2010) included in their multi-objective formulation price, lead-time and VaR-type risk of disruption as four conflicting objectives that must be minimized simultaneously. The solution is based on goal programming. Baron et al. (2011) developed a robust multi-period UFL for which the number of facilities, their location and capacities, the production rates in each period, and the allocation of demand to facilities should be determined. Gulpinar et al. (2012) formulated a stochastic model for multiple capacity facilities that serve customers with a single product, and treated stock-out probabilistic requirement as a chance constraint.

Based on robust optimization, they presented numerical experiments to illustrate the performance of the different robust formulations.

Pishvaei et al. (2012) presented a robust programming approach to socially responsible supply chain design. Hahn and Kuhn (2012) analyzed value-based performance and risk management in supply chains with the help of robust optimization. Sawik (2013, 2017) developed a stochastic programming model for integrated supplier selection, order quantity allocation and customer order scheduling in the presence of supply chain disruption risks. In the study by Madadi et al. (2014), a problem of supply network design under risk of supply disruptions was considered. Disruptions resulting from tainted materials delivery are modeled as events which occur randomly and may have a random length. A mixed-integer stochastic model was proposed and solved by a meta-heuristic algorithm. Torabi et al. (2015) proposed a bi-objective, mixed, two-stage stochastic programming model for supplier selection and order allocation problem under operational and disruption risks. The model considers several proactive strategies such as suppliers' business continuity plans, fortification of suppliers and contracting with back-up suppliers.

5.4 Pricing and Game Theory

Competition, pricing and contracting issues attracted wide attention from researchers in the fields of pricing theory, inventory control, and game theory. Babich et al. (2007) studied the effects of competition and diversification in supply chain with supplier default risk. Hennet and Arda (2008) applied game theory to supply chain coordination. Serel (2008) modelled inventory and pricing decisions in a single-period problem faced by one retailer and two suppliers, where one supplier encounters supply disruption risks. Li et al. (2010b) investigated the sourcing strategy of a retailer and the pricing strategies of two suppliers in the case of a supply disruption. They derive a coordination mechanism to maximize supplier profits.

Hou et al. (2010) analyzed coordination with a back-up supplier through a buy-back contract during supply disruption. Kouvelis and Li (2012) elaborated on the optimal parameter setting for two strategies, i.e., the ex-ante planning for disruption safety stock to be released when a "disruption" occurs (in this case, late delivery of the order) and the ex-post dynamic emergency response, which decides on the timing and size of the emergency order to be placed. They compared the added values when used to complement the traditional safety lead-time approach, and examined how the use of contingency strategies affects the safety lead-time and corresponding cycle length of a periodic review system.

Gümüs et al. (2012) analyzed the issues and effects of supplier selection based on price and quantity guarantees for unreliable suppliers. Wakolbinger and Cruz (2011) considered strategic information sharing and risk-sharing contracts for

supply chain disruption risk management. Li et al. (2013b) analyzed how pricing power affects a firm's decisions to source from unreliable suppliers.

Federgruen and Yang (2011) presented a general periodic review model to analyze the dynamic effects of inventory buffers in the event suppliers are unreliable. Qi (2013) developed a continuous review inventory model with random disruptions at the primary supplier. Hishamuddin et al. (2013) presented a recovery model for a two-echelon serial supply chain with consideration of transportation disruption. Their model is capable of determining optimal ordering and production quantities during the recovery period to minimize total costs.

From a game-theoretical perspective, Gupta et al. (2015) studied the implications of a contingent sourcing strategy under competition and in the presence of a possible supply disruption. The time of the occurrence of the supply disruption is uncertain and exogenous, but the procurement time of components is in the control of the firms. The results imply that supply disruption and procurement times jointly impact firms' buying decisions, optimal order quantities and their expected profits. Subsequently, this study considers the impact endogenizing equilibrium sourcing strategies of asymmetric and symmetric firms, and of capacity reservation to mitigate disruption.

5.5 Simulation

While mathematical and stochastic optimization dominate the research domain in supply chain disruption management, the potential of simulation modelling still remains underexplored. At the same time, simulation is a recognized approach to modelling supply chain and logistics dynamics (Deleris and Erhun 2005; Longo and Mirabelli 2008; Tako and Robinson 2012; Meisel and Bierwirth 2014; Oliveira et al. 2016; Ivanov 2017b).

Simulation literature considers the ripple effect in the supply chain from five different methodical perspectives (Ivanov 2017a):

- System dynamics
- Agent-based modelling
- Discrete-event simulation
- Graph-theory based simulation
- Optimization-based simulation.

Simulation studies on supply chain disruption risks naturally play an important role in research communities since they are able to handle time-dependent and gradual disruption duration, duration of recovery measures, capacity degradation and recovery.

5.5.1 *System Dynamics*

First, *system dynamics* has been applied to simulate the ripple effect in the supply chain. Wilson (2007) considered transportation disruptions in a multi-stage supply chain to show the impact of the ripple effect on fulfilment rate and inventory fluctuations. The findings suggest that transportation disruptions between the Tier-1 supplier and the warehouse have the highest impact on performance. Further, this study depicts the value of VMI (vendor-managed inventory) for disruption mitigation. Bueno-Salano and Cedillo-Campos (2014) simulated a specific case of the ripple effect, so called “border effect” in the Mexico-U.S. trade that may occur if products cross land borders or arrive through seaports. The authors included three disruption durations scenarios at an international border (3, 8, and 10 days in out-of-operation mode respectively) and simulated the impact of an inventory increase to overcome the effect of such disruptions on total supply chain costs. The main finding of this study is the exponential increase of total supply chain costs subject to increasing disruption duration (0.1% costs increase for 3 days of disruption, 130% for 8 days of disruption, and 472% for 10 days of disruption). This is in line with results obtained by Wilson (2007).

5.5.2 *Agent-Based Simulation*

Second, *agent-based simulation* has been used to model supply chain disruptions and their impact on supply chain performance. Xu et al. (2014) modelled disrupted capacities at suppliers in a three-stage supply chain and considered recovery policies and their impacts on the supply chain service level. The authors used AnyLogic multimethod simulation software. The authors compared performance impact with and without recovery measures for four scenarios. The results indicate the ripple effect’s impact on customer satisfaction depends not only on recovery measures, but also on proactive resilience planning. One interesting insight of this study is the explicit identification of “retailer-supplier” links that are especially sensitive to disruptions at the suppliers. Blos et al. (2015) presented a framework for agent-based modelling of supply chain disruptions and focused on the process of agent refinement.

5.5.3 *Discrete-Event Simulation*

Third, *discrete event simulation* has been used for study of severe disruptions in the supply chain and resilience analysis. Carvalho et al. (2012) analyzed a four-stage supply chain based on the real-life case study of a Portuguese automotive supply chain. Focusing on how different recovery strategies influence supply chain

performance in the event of disruptions, the authors analyzed two recovery strategies and six disruption scenarios. The scenarios differ in terms of presence or absence of a disturbance and presence or absence of a mitigation strategy. The performance impact regarding lead time ratio and total supply chain costs has been analyzed using the ARENA-based simulation model.

Schmitt and Singh (2012) presented a quantitative estimation of disruption risk in a multi-echelon supply chain using discrete-event simulation. The disruption risk was measured by “weeks of recovery” as the amplification of the disruption. The modelled proactive and recovery strategies included satisfying demand from an alternate location in the network, procuring material or transportation from an alternative source or route, and holding strategic inventory reserves throughout the supply chain. In regard to the ripple effect, this study provides two interesting results. First, increases in the inventory levels of raw material and finished goods in anticipation of disruptions significantly exceed those required when only stochastic demand is considered. Second, “upstream disruptions in the supply chain may not be felt as quickly as downstream disruptions, but their impact can be amplified, outlasting the disruptions themselves.” The authors also showed that the employment efficiency of back-up mitigation methods depend on the response speed.

Lewis et al. (2013) analyzed the disruption risks at ports of entry with the help of closure likelihood and duration, which were modelled using a completely observable, exogenous Markov chain. They developed a periodic review inventory control model that indicates, for the scenarios studied, that operating margins may decrease 10% for reasonably long port-of-entry closures or be eliminated completely without contingency plans, and that expected holding and penalty costs may increase 20% for anticipated increases in port-of-entry utilization.

Hishamuddin et al. (2015) simulated a three-echelon inventory system in the supply chain with multiple sourcing and considered both supply and transportation disruptions. They included disruption duration, recovery costs and a random disruption generator in the model. The most important finding of this study is that backorder quantity and recovery duration have strong positive correlations with total supply chain costs as compared to the importance of lost sales. This study contributes to the body of knowledge on the ripple effect in the supply chain by demonstrating that disruptions between the supplier and manufacturer imply higher average supply chain costs as compared to disruptions between the producer and distributor. At the same time, the authors revealed that the impact on performance of both recovery duration and disruption location are quite similar for supply and transportation disruptions. This result is in line with the study by Yu et al. (2009).

Ivanov et al. (2016c) developed a discrete-event simulation model to analyze time critical supply chains in the Australia dairy industry and recovery policies in the presence of the ripple effect. They simulated reactive recovery policies in the dairy supply chain under conditions of the ripple effect to compare proactive and reactive approaches to tackling the ripple effect from the point of view of resilience and flexibility.

Ivanov (2017a) considered a four-stage SC that comprises a manufacturer, a central distribution centre, two regional distribution centres and ten customers in

different European cities. Using anyLogistix software, a discrete-event simulation model for the ripple effect analysis has been developed. The results suggest that the ripple effect enhances the impact of disruptions on performance. Upstream disruptions are more likely to result in the ripple effect in the case of single sourcing policy. A safety stock increase is recommended at facilities downstream of disruption-risky SC elements. Higher inventory levels in the downstream SC dampen propagation of the ripple effect towards the customers. At the same time, a safety stock increase at disruption-risky facilities should be considered carefully, since if these facilities are not able to perform outbound operations (e.g. fire or strike) the increased safety stock is not useful for alleviating the ripple effect. Moreover, it has been observed that ripple effect has higher impact on service level and order fulfilment than disruption duration. This implies that dual sourcing at SC bottlenecks and large inventory holding points downstream of disruption-risky facilities is more important than hasty investments in quick recovery.

Ivanov (2017b) developed a discrete-event simulation model in anyLogistix to study the interfaces of the ripple effect and sustainability. A multi-stage SC with suppliers, factory, distributions centres, and customers was considered. This study helps to identify what sustainability factors mitigate or enhance the ripple effect in the SC. The results indicate that (i) sustainable, single sourcing enhances the ripple effect; (ii) facility fortification at major employers regionally mitigates the ripple effect and enhances sustainability; and (iii) a reduction in storage facilities in the SC downstream of a disruption-risky facility increases sustainability, but causes the ripple effect. In addition, the results depict a time lag between recovery launch and recovery impact on service level gap reduction. This leads to the conclusion that proactive policies in the SC need to be designed in regard to disruption durations. Moreover, the results indicate that human factors need to be involved in regard to coordination complexity analysis and recovery impact on disruption duration. With the help of Big Data, Ivanov (2017c) developed a discrete-event simulation model in anyLogistix to study the impact of demand pattern identification on ripple effect mitigation in the SC. Four managerial strategies were proposed for different demand and inventory control patterns.

5.5.4 Graph-Theoretical Studies

Fourth, *graph-theoretical simulation* studies need to be addressed. Petri nets were applied to analyze disruption propagation through the supply chain and to evaluate the performance impact of the disruptions (Wu et al. 2007). Tuncel and Alpan (2010) extended the body of knowledge by incorporating multiple disruption scenarios (disruptions in demand, transportation and quality). In addition, this study also considers recovery actions and the performance impact of such mitigation strategies. Zegordi and Davarzani (2012) applied colored Petri nets in order to

improve the visualization abilities of simulation models. The study by Lin et al. (2014) concentrates on a reliability assessment for a multi-state supply chain with multiple suppliers as the probability of satisfying market demand within budget and production capacity limitations. They developed an algorithm in terms of minimal paths to evaluate network reliability along with a numerical example applied to an auto glass manufacturer. Garvey et al. (2014) built upon a minimal paths analysis and suggested using a Bayesian network to analyze risk propagation in the supply chain. This is an interesting research avenue since Bayesian networks have been applied to domino effect analysis in chemical industry infrastructures (Khakzad 2015).

Kim et al. (2015) applied graph theory to analyze the impact of supply chain structure on resilience. This study reveals that the network structure significantly determines the likelihood of disruption. Sokolov et al. (2016) quantified the ripple effect in the supply chain with the help of selected indicators from graph theory subject to disruption propagation in a multi-stage distribution network. Han and Shin (2016) assessed the supply chain structural robustness considering disruption propagation in a connected graph. They performed a quantitative assessment of structural robustness on random networks compared to the probability of network disruption due to the random risk. Tang et al. (2016) developed a time-varied cascading failure model and analyzed the ripple effect as failed loads propagation in the supply chain. They presented the supply chain as an interdependent structure of an undirected cyber network and a directed physical network, two layers that constitute a supply chain. The authors developed a robustness measure and analyzed the supply chain collapse situations.

5.5.5 *Optimization-Based Simulation*

Fifth, *optimization-based simulation* studies should be addressed. Benyoucef et al. (2013) considered a two-period supply chain design model in which selected suppliers are reliable in the first period and can fail in the second period. The corresponding problem of facility location/supplier reliability is formulated as a non-linear stochastic programming problem. The authors used a Monte Carlo approach in combination with Lagrangian relaxation. Lim et al. (2013) turned away from probability estimation issues and faced the trade-off of under- vs overestimation of disruption probabilities. Simulation results provide evidence that underestimation of disruptions may have a significantly higher impact on the total supply chain costs than overestimation. Such analysis has been performed on the basis of a stylized continuous location model.

Lee et al. (2014) simulated supply forecasts during supply chain disruptions. Ivanov et al. (2014a) used a hybrid optimization-control model for simulation of supply chain recovery policies for multiple disruptions in different periods in a

multi-stage supply chain. The developed approach allows simultaneous analysis of the impact of supply chain disruptions and different simulations of recovery policies on performance. Schmitt et al. (2015) investigated the effects of demand uncertainty and disrupted supply. In contrast to classical results on risk pooling in multi-stage inventory systems, the authors found out that a decentralized inventory system performs better for deterministic demand and stochastic supply. For the case of stochastic demand and supply, they also recommended using a decentralized inventory system if the decision maker is risk-averse.

Chávez et al. (2017) considered transportation disruption within a multi-objective stochastic optimization model in regard to freight costs and lead time minimization. The authors analyzed a special case of products, i.e., perishable goods. Hasani and Khosrojerdi (2016) developed a non-linear mixed-integer programming model and used it to simulate resilience strategies to mitigate the risk of correlated disruptions. Ivanov et al. (2016a) extended performance impact assessment and supply chain plan reconfiguration with consideration of the duration of disruptions and the costs of recovery. They analyzed seven proactive supply chain structures, computed recovery policies to re-direct material flows in the case of two disruption scenarios, and assessed the impact on performance for both service level and costs with the help of a supply chain (re)planning model containing elements of control theory and linear programming. This study reveals the impact of different parametrical and structural resilience measures on supply chain service level and efficiency.

5.6 System Science and Control Theory

An important part of supply chain management issues is concerned with the supply chain dynamics at the system, structural and parametrical levels. Let us list a few of them. First, the issues of performance and uncertainty regarding the balance of efficiency, complexity, flexibility and robustness should be mentioned (Stevenson and Spring 2007; Meepetchdee and Shah 2007; Wadhwa et al. 2008). Second, the problem of “modelled” optimality and real-life executability and adaptability is under consideration (Krajewski et al. 2005; Chauhan et al. 2007). Third, the problem of sustainability, i.e. balancing economic gains with environmentally friendly resource and energy consumption is crucial. In observing these challenges, it becomes evident that an important part of supply chain management problems is related to changes in the supply chain environment and reacting to these changes: that is, with supply chain dynamics.

Another challenge is supply chains with both continuous and discrete processes. Such supply chains are typical in oil, gas or chemical industry, etc. (Dessouky et al. 1999; Shah 2005; Puigjaner and Lainez 2008). In optimizing these supply chains, methods must consider both processes. In addition, even the supply chains with only discrete processes frequently contain different technological feedbacks, re-manufacturing processes, etc. along their product lifecycle.

Finally, the achievement of planned supply chain performance can be inhibited by changes and perturbations in real life situations (Kleindorfer and Saad 2005). Therefore, supply chains need to be reliable and flexible enough to be able to adapt their behavior when disturbed and remain stable and resilient.

Understanding the importance and impact of dynamics and vulnerability on the performance and resilience of supply chains is becoming ever more important in literature, theory and practice. Control and system theoretic approaches have been proved suitable tools for the analysis of supply chain design in terms of the uncertainties, disruptions, and the bullwhip and ripple effects.

Despite the fact that significant advances have been made in supply chain optimization, the domain of dynamics merits more systematic and critical attention. Although it is intuitive that dynamics is likely to have impacts on profitability, there is little systematic analysis and documentation of the magnitude of these impacts in the literature both (1) at the planning stage while synthesizing supply chains in anticipation of uncertainty and analyzing these plans in different execution environments and (2) at the execution control stage while adapting supply chains. From these perspectives, the extensive development of approaches and models to tackle supply chain dynamics and considering supply chain planning and scheduling in terms of execution dynamics, adaptation and robustness is becoming a critical topic in supply chain management. A possibility for addressing the above-mentioned challenges is the use of the control theoretic approach.

In reviewing the literature, two major control theoretic methods are observed, i.e.:

- Dynamic production-inventory control; and
- Optimal program control.

Let us consider the existing literature on these domains as an extension of the analysis presented in the study by Ivanov et al. (2012).

5.6.1 Dynamic Feedback Production-Inventory Control

Beginning with the first study published on using calculus of variations to solve production-inventory problems by Holt et al. (1960), integrated production-inventory problems with lot-size and capacity optimization have been extensively considered (Axsäter 1985; Feichtinger and Hartl 1985; Axsäter and Rosling 1993; Ortega and Lin 2004; Schwartz and Rivera 2010). With the help of linear classical control theory, Disney and Towill (2002) and Hoberg et al. (2007) recently investigated the effects of inventory control policies on order and inventory variability. Bensoussan et al. (2007) considered possible information delay and incompleteness in ordering policies for inventory decisions.

Previous models and an additional literature overview can be found in the work by Sethi and Thompson (2000). However, the authors frequently point out certain limitations in linear control theory analytics. For example, linearity requires strong

assumptions regarding demand backordering and negative orders (i.e. physical returns), and imposes heavy burdens on possible relationships between parameters. These limitations can be eliminated by the advantages of system dynamics theory, as shown in Villegas and Smith (2006) on analysis of inventory and order oscillations trade-off. One of the advantages of system dynamics is that it deals with the non-linear issues of supply chain dynamics. For further reading on application of classic control theory to logistics and supply chain management, please refer to the studies by Ortega and Lin (2004) and Sarimveis et al. (2008).

A very extensive area of control theory applications to supply chain management is related to adaptation and real-time control. It is the point of reference for many supply chain scholars and professionals when first discussing control theory. A popular technique of supply chain adaptive planning is the *model predictive control*. In model predictive control, a system model and both current and historical measurements of the process are used to predict system behavior at future instants. A control-relevant objective function is then optimized to calculate a control sequence to satisfy the system constraints. The model predictive control approach is not simply for running the planning frequently, but rather for developing decision policies (Wang et al. 2007).

Applications of model predictive control to multi-echelon production–inventory problems and supply chains have been examined previously. Perea et al. (2000) modeled a multi-plant, multi-product polymer process through difference equations and a schedule optimization in model predictive control framework. Braun et al. (2003) developed a decentralized model predictive control implementation for a six-node, two-product and three-echelon demand network problem. In the study by Puigjaner and Lainez (2008), a multi-stage stochastic model was employed. However, the stabilizing controllers remain a critical bottleneck in model predictive control (Mayne et al. 2000).

Ivanov et al. (2013, 2014b) developed a model for multi-period and multi-commodity supply chain design with consideration of structure dynamics. The original idea of these studies is to describe the supply chain as a non-stationary dynamic control system with a linear programming model. In the model parameter, Mastragostino et al. (2014) analyzed supply chain performance in the presence of uncertainty where demand was subject to service level in the supply chain. Fu et al. (2015) used an extended prediction, self-adaptive control ordering policy for quantifying and mitigating the bullwhip effect in a benchmark supply chain system. Sagawa and Nagano (2015) used a dynamic approach to model the dynamics of a multi-product manufacturing system in application to a real case. Ivanov et al. (2014a, 2016a) included speed and time of recovery and developed a hybrid control-based model blended with linear programming in order to analyze different proactive supply chain designs and recovery policies in regard to multiple performance impact.

When applying model predictive control to supply chain management, the centralized controller and its functions are essential. In technical systems, the controller is a technical device (e.g., a sensor) that adapts the system behavior based on error identification within milliseconds. The controller in the supply chain

is a manager, or more precisely, several managers with possible conflicting interests. Even if a deviation in the supply chain execution was identified (e.g., track delay identification with the help of RFID or supply chain event management), the model predictive control controller will not be able to change anything in this situation. Therefore, models are needed to identify the deviations and notify the supply chain managers. This is used to estimate the impact of the disturbance on supply chain performance, and to produce recommendations on adaptations. Additional research is needed to analyze the applicability of model predictive control to human-driven supply chains.

Another fundamental aspect of supply chain management is an analysis of randomness, disturbances and fluctuations (Louly and Dolgui 2002; Louly et al. 2008). There is considerable variation in the definitions of terms related to supply chain uncertainty, robustness, stability and performance (Klibi et al. 2010). Basically, there are three main properties of a supply chain which can be analyzed regarding uncertainty. These are the following: (1) ability to cope with volatility and continue plan execution after being perturbed, (2) ability to remain stable and achieve the planned performance in the presence of disturbances, and (3) ability to maintain, execute and recover (adapt) planned execution along with the achievement of the planned (or adapted, but yet still acceptable) performance. In the systems and control theories, these properties are analyzed as *stability* (property 1), *robustness* (property 2), and *disaster-tolerance* (property 3).

Understanding stability depends much on the system considered as well as on the methods and goals of systems analysis. Disney and Towill (2002) applied a discrete linear control theory model to determine the dynamic stability of vendor managed inventory supply chains. The study by Daganzo (2004) applied classical control theory and Lyapunov's stability metrics to the supply chain management domain. Warburton et al. (2004) provided a stability boundary for the continuous time supply chain ordering decision with regard to BIBO (bounded-in-bounded-out) stability. In some studies, the bullwhip-effect has been addressed from the control theoretic perspective (Dejonckheere et al. 2004; Ouyang and Li 2010). Decentralized supply networks have also been considered in recent research (Scholz-Reiter et al. 2010). Schoenlein et al. (2013) applied stability analysis based on multiclass queuing network. The authors studied different destabilization inputs and formulated a mathematical program that minimizes the required network capacity, while ensuring a desired level of robustness.

Although stability analysis is a useful tool, it is subject to many restrictions if applied in the classical form of Lyapunov's stability or BIBO stability. First, these standard models imply the natural movement of objects. Second, they typically consider very small deviations of control and output variables. Third, stability analysis can help in estimating supply chain volatility in any concrete state. But it is not enough to stabilize the supply chain – the supply chain should also bring profit; hence, the inclusion of performance considerations (i.e., the robustness analysis) is required as the next step. Finally, classical stability analysis is concerned with funding equilibrium states for mechanical and automatic systems, but not organizational systems.

Yang and Fan (2016) compared the disruption mitigation effects of three information management strategies with the help of control theory. From the perspective of stability, the existing stability boundaries are revised by a new method in a two-echelon case. Spiegler et al. (2012, 2016a, b) developed a method to use nonlinear control theory in the dynamic analysis of supply chain resilience in the empirical context of a grocery supply chain and analyzed the value of nonlinear control theory to investigate underlying supply chain dynamics. The method developed provides insights into nonlinear system control structures, including a better understanding of the influence of control parameters on dynamic behavior and the impact of nonlinearities on supply chain performance. Ivanov et al. (2016b, c) applied attainable sets to the analysis of supply chain design and schedule resilience in optimal program control framework. Recent application of feedback error-based control methods to production-inventory and supply chain problems can be encountered in the works by (Wang et al. 2012; Spiegler et al. 2012, 2016a, b).

5.6.2 *Optimal Multi-stage Production Planning and Scheduling*

Optimal design, planning and scheduling is another application of control theory, and especially optimal program control, to supply chain management. *Optimal program control* is a method for solving dynamic optimization problems, when those problems are expressed in continuous time and the values of goal criteria vector $\mathbf{J}$ are accumulated over time subject to changes of a state vector $\mathbf{x}(t)$ under the influence of constrained control actions $\mathbf{u}(t)$. Optimal program control is a deterministic control method as opposite to stochastic optimal control (Fleming and Rishel 1975). One of the basic milestones in modern optimal program control, along with dynamic programming (Bellmann 1972), is the *maximum principle* that was developed in 1950s by Russian mathematicians (Pontryagin et al. 1964).

Specific large scale scheduling problems with complex hybrid logical and terminal constraints, process execution non-stationarity, complex interrelations between process dynamics, capacity evolution and setups require further investigation and the attraction of a broad range of methodical approaches. One of these approaches is optimal control with applications for scheduling in production, supply chain and Industry 4.0 systems.

Optimal control approaches take another perspective as mathematical programming methods where schedules are represented as trajectories. The system state vector is determined by the evolution of state variables $x(t)$ that characterize the system at each point of time. The state evolution in dynamics is determined by the control variables $u(t)$ that correspond to the decisions of a person or an algorithm governing the system dynamics. In real-life control engineering, control variables are typically considered bounded piece-wise continuous functions. Examples of controls in supply chain systems are processing rates at machines in manufacturing

or shipment rates in transportation. In production scheduling, binary control variables can be used which describe the assignment of a job to machine.

The optimal program control vector $\mathbf{u}(t)$ and the state trajectory $\mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t)$ should be determined so that the boundary conditions are met; in other words, the desired values of the scheduling performance indicators should be achieved as an analogy to goal programming (see Chap. 7).

The peculiarity of optimal control models are constraints. In practice, the system trajectory cannot belong to some areas in the state space. The above-mentioned boundary conditions belong to the constraints on the trajectory that can differ in regard to fixed or free ends. In scheduling models, we typically have fixed boundary conditions. The second group builds the constraints on control. Since the search for optimal control is performed in the class of functions $u(t)$ that depend only on t , this problem class is called optimal program control. Typically, in production scheduling we have optimal program control problems with two types of constraints on control, i.e., terminal and logical constraints.

Terminal constraints describe limited control resources (Maimon et al. 1998). An example of a terminal constraint is capacity restriction at a machine. Logical constraints describe α -precedence relations of the type “or” and precedence relations of the type “and” in regard to the operation sequences in the jobs (Ivanov and Sokolov 2010). Sethi et al. (2002) and Khmelnitsky et al. (2011) extended the idea of the maximum principle to a stochastic environment that could be of use in the analysis of stochastic scheduling problems.

Necessary optimality conditions can be derived from the maximum principle (Sethi 1978; Hartl et al. 1995; Afanasiev et al. 1996; Maimon et al. 1998; Ivanov and Sokolov 2010). Pontryagin’s maximum principle is an original method for computing optimal program control when optimizing system behavior over many time periods under constrained control, subject to several decision variables where other techniques can become analytically and computationally difficult to apply. The initial formulation of the maximum principle was applied to the problem transferring a space vehicle from one orbit to another with minimum time and minimum fuel consumption.

According to the maximum principle, the optimal solution of instantaneous problems can be shown to give the optimal solution to the overall problem (Pontryagin et al. 1964; Boltyanskiy 1973; Hartl et al. 1995; Sethi and Thompson 2000). The maximum principle basically generalizes the calculus of variations and builds the basis of optimal program control theory. The development of the maximum principle has stimulated the application of optimal program control to many industrial and engineering areas of research and implementation.

Typically, computational procedures start with a nominal solution that satisfies both the main and conjunctive differential systems. Then, this solution is modified by integrating the main and conjunctive systems by control variations toward the Hamiltonian increase. During this procedure, at $t = T_f$ transversality conditions are evaluated. Transversality conditions are the end conditions of the conjunctive system. The conjunctive variables can be interpreted as dynamic priorities of jobs and play here the same role as “shadow” prices in linear programming models.

However, in contrast to those canonical forms where the “shadow” prices are fixed, the conjunctive variables change dynamically. These changes are subject to the contribution of a particular operations assignment and scheduling (i.e., machine and time windows) to the performance assessment functions. Consequently, at each point of time, the dynamic priorities of jobs may be changed if a newly arrived job provides a better contribution to the performance.

Articles by Fan and Wang (1964) and Hwang et al. (1967) were among the first studies on the application of the discrete maximum principle to multi-level and multi-period master production scheduling and inventory control. Hwang et al. (1967) determined production planning as optimal control action and the corresponding trajectory of state variables (the inventory) by means of the maximum principle subject to minimization of costs.

The stream of production scheduling was continued by Kinemia and Gershwin (1983), who applied a hierarchical method in designing the solution procedure to the overall model, and Khmel'nitsky et al. (1997) and Kogan and Khmel'nitsky (2000), who applied the maximum principle in discrete form to planning continuous-time flows in flexible manufacturing systems and transited from the hierarchical approach to heuristic rules for optimal program control calculation. Thompson et al. (1984) applied optimal control to develop a planning and forecasting model with simultaneous price and production decisions.

Although the application of optimal program control has been widely understood at the tactical planning level, research on optimal program control for detailed dynamic production and transportation scheduling in the integrated supply chain context is fairly recent. Nevertheless, there is a wealth of publications on these topics from the perspective of operations research. This rapidly emerging field of integrated, customer-oriented supply chain scheduling (Ivanov and Sokolov 2012) can become a new area for applying optimal program control for supply chain management.

Advantages of optimal program control methods can be considered in regard to treatment of large scale problems with complex constraints, consideration of non-stationary process execution dynamics, representation in differential equations of complex interrelations between process execution, capacity evolution and machine setups. In addition, accuracy of continuous time and accurate presentation of continuous flows (e.g., in process industry or energy systems) with the help of continuous state variables belong to optimal control advantages. Finally, and probably most important, schedule presentation in terms of optimal control opens constructive ways to incorporate the rich variety of control theoretic axioms in regard to feedback adaptive control (mostly applied in the framework of production-inventory control models) as well as use of control tools for qualitative performance analysis such as attainable (reachable) sets.

The limitations of control applications should also be addressed. Control applications are conceptually restricted to modelling mostly continuous flows and have computational restrictions in regard to the possible numerical instability, Heaviside step function jumps, nonexistence and non-convexity of gradients, gradient step and quality of nominal control vector. The algorithmic method selection strongly

depends on the form of the process model and constraint. That is why the state-of-the-art in optimal control mathematics does not provide a general framework for all application areas but rather serves to develop concrete solutions for concrete applications cases using complexes of proven theorems and axioms.

In regard to future research and in light of the shown methodical shortcomings and application limitations of optimal control methods using the maximum principle, the following research avenues can be explored further. First, concrete application cases need to be considered for which specific control models and algorithms will be developed. The construction of models and computational procedures within proved axiomatic of control theory is important. Second, application of qualitative performance analysis methods for control policy dynamic investigation under uncertainty such as attainable sets needs to be studied further. These tools might be helpful in regard to the analysis of production schedule robustness, supply chain resilience and Industry 4.0 system flexibility. Third, computational methods themselves need to be further investigated and modified for concrete application to cases. A closer collaboration of control and industrial engineers is therefore an important requirement of future applications of control methods in operations and supply chain management.

5.7 Analysis and Observations

5.7.1 *Reasons for Supply Chain Risks*

Numerous qualitative analysis studies including (but not limited to) the works of Hendricks and Singhal (2005), Kleindorfer and Saad (2005), Craighead et al. (2007), Blackhurst et al. (2011), Bode et al. (2011), Simangunsong et al. (2012), Pettit et al. (2013), Tang et al. (2014), and Ambulkar et al. (2015) revealed basic reasons for disruptions and their impact on supply chain execution and performance. For example, Chopra and Sodhi (2004) categorized potential supply chain risks into nine categories: (a) disruptions (e.g. natural disasters, terrorism, war, etc.); (b) delays (e.g. inflexibility of supply source); (c) systems (e.g. information infrastructure breakdown); (d) forecast (e.g. inaccurate forecast, the bullwhip effect, etc.); (e) intellectual property (e.g. vertical integration); (f) procurement (e.g. exchange rate risk); (g) receivables (e.g. number of customers); (h) inventory (e.g. inventory holding cost, demand and supply uncertainty, etc.); and (i) capacity (e.g. cost of capacity).

Sodhi and Lee (2007), Hendricks et al. (2009) and Stecke and Kumar (2009) considered bankruptcies at suppliers and logistics companies. Kleindorfer and Saad (2005) and Sodhi et al. (2012) included environmental regulations in supply chain risks considerations. Trade and customs regulations were also considered in the studies by Craighead et al. (2007) and Stecke and Kumar (2009). Hallikas et al. (2004), Knemeyer et al. (2009), Bode et al. (2011) and Christopher et al. (2011)

underlined the importance of contingency plans. Chopra and Sodhi (2004) and Craighead et al. (2007) also considered demand disruption risks as consequences of currency exchange rate fluctuations.

In some studies (Knemeyer et al. 2009; Soroor et al. 2009; Tang and Musa 2011) information system disruptions were analyzed. The works (Hendricks and Singhal 2005; Knemeyer et al. 2009; Bode et al. 2011; Christopher et al. 2011; Tang and Musa 2011; Sodhi et al. 2012; Chen et al. 2013) deal with the importance of collaborative information systems for risk management in supply chains. Pyke and Tang (2010) and Steven et al. (2014) considered quality problems in end products. Chaudhuri et al. (2013) added new product development and time-to-market risks. Supply chain risk management as a part of supply chain organization has also been considered in studies (Sheffi and Rice 2005; Knemeyer et al. 2009; Blackhurst et al. 2011; Pettit et al. 2013; Schmidt and Simchi-Levi 2013) as an important driver of timely and efficient recovery.

In Table 5.1, we show how different causes of uncertainties and supply chain risks (as identified in empirical literature) have been addressed in quantitative analysis literature.

Literature on proactive strategies for supply chain disruption management suggests different approaches to generate robust and resilient supply chain structures. Studies by Snyder and Daskin (2005), Goh et al. (2007), Wilson (2007), Wu et al. (2007), Cui et al. (2010), Ravindran et al. 2010; Peng et al. (2011), Yang et al. (2012), Ahmadi-Javid and Seddighi (2013), Baghalian et al. (2013), Benyoucef et al. (2013), and Xu et al. (2014) are recommended references on the proactive approach.

Investment in supply chain protection can help to avoid many disruptive problems. However, it is impossible to totally avoid disruption. Simchi-Levi et al. (2014) emphasized that focus should be directed to recovery policies regardless of what caused the disruption. Therefore, adaptation is needed to change supply chain plans, schedules or inventory policies in order to achieve the desired output performance even during or after a disruption.

5.7.2 *Risk Mitigation and Recovery Measures*

It should be noted that the scope of rippling and its impact on economic performance depends both on robustness reserves (e.g., redundancies like inventory or capacity buffers) and speed and scale of recovery measures (Hendricks and Singhal 2005; Sheffi and Rice 2005; Tomlin 2006; Bode et al. 2011; Ivanov and Sokolov 2013; Kim and Tomlin 2013).

In many practical settings, companies need analysis tools to estimate the impacts of recovery measures subject to different disruptions and performance indicators. Such recovery options comprise facility fortification (e.g., back-up suppliers, warehouses, depots and transportation channels), inventory and capacity expansion. Contingency plans or back-up planning (e.g., alternative suppliers or shipping

Table 5.1 Reasons for uncertainties and supply chain risks

Operational uncertainty and risks				Disruption uncertainty and risks		
Uncertainty						
Demand	Supply	Product	Regulations	Demand	Supply chain structure	
Demand uncertainty	Supply uncertainty	Product quality and variety uncertainty	Legal uncertainty	Financial and political crises	Natural and man-made disasters, strikes, piracy	
Risks						
Demand	Supply	Product	Regulations	Demand	Supply chain structure	
Demand fluctuations (Lee et al. 1997; Chen et al. 2000; Perea et al. 2000; Daganzo 2004; Santoso et al. 2005; Villegas and Smith 2006; Acar et al. 2010; Hsu and Li 2011; Lin and Wang 2011; Kumar and Tiwari 2013; Kılıç and Tuzkaya 2015)	Lead-time and order quantity fluctuations (Acar et al. 2010; Hsu and Li 2011; Kouvelis and Li 2012; Paul et al. 2014)	Product recalls, end-product quality problems (Dai et al. 2015)	Environmental regulations	Demand disruption (Goh et al. 2007; Azaron et al. 2008; Baghalian et al. 2013)	Production facility disruption (Snyder and Daskin 2005; Azaron et al. 2008; Cui et al. 2010; Klibi et al. 2010; Qi et al. 2010; Baron et al. 2011; Schmitt and Singh 2012; Ivanov et al. 2013; 2014a, b; Li et al. 2013a; Lim et al. 2013)	
Product variety (Teimoury and Fathi 2013; Zhou et al. 2013; Meisel and Bierwirth 2014)	New product development	Quality problems in raw materials	Trade and customs regulations	Supplier and logistics service provider bankruptcy	Transportation disruption (Wilson 2007; Klibi et al. 2010; Peng et al. 2011; Ivanov et al. 2013; Lewis et al. 2013)	

Information coordina- tion (Lee et al. 1997; Chen et al. 2000; Ouyang and Li 2010)		Changes in product configuration (Lu et al. 2011; Chern et al. 2014)	Thefts and damage (Li et al. 2010a; Lin et al. 2014; Validi et al. 2014)	Currency exchange rates fluctuations	Supply disruptions (Yu et al. 2009; Ravindran et al. 2010; Federguen and Yang 2011; Benyoucef et al. 2013; Sawik 2013)
					Information system disruptions (Ivanov et al. 2014c)

routes) need to be developed (Knemeyer et al. 2009; Cui et al. 2010; Yang et al. 2012; Benyoucef et al. 2013; Li et al. 2013a). Recovery must happen quickly to expedite stabilization and adaptation in order to ensure supply chain continuity and avoid long-term impact. In implementing such recovery policies, companies need a tool, supported by collaboration and supply chain visibility solutions, for assessing the impact of disruption on the supply chain as well as the effects of redirecting material flows (Sheffi and Rice 2005; Chopra and Sodhi 2014; Simchi-Levi et al. 2014).

In Table 5.2, we show how different methods for supply chain risk mitigation and recovery (as identified in empirical literature) have been addressed in quantitative analysis literature.

Basic areas of *flexibility* include system, process and product (Skipper and Hanna 2009; Simchi-Levi and Wei 2015). Inventory and capacity buffers can be considered as *parametrical redundancy*. Back-up facilities and supplier belong to *structural redundancy*. Supply chain localization and segmentation assumes a combination of local and global sourcing. For example, ZARA produces their trendiest items in Europe close to a highly dynamic and changing demand. Alternatively, slow-moving items are produced in Turkey and Asia since lead-time is not crucial and cost reduction can be achieved in manufacturing. Li & Fung Ltd., a contract manufacturing company from Hong Kong, has a variety of supply plans that enable flexible shifting of production among suppliers.

Many companies also invest in structural redundancy (e.g., Toyota extends its supply chain subject to multiple sourcing and building new facilities on the supply side). Focusing on single sourcing provides many efficiency advantages. However, a number of recent disruptions have forced supply chain managers to rethink this lean sourcing strategy since the cost savings can be wiped out by disruption impacts (Chopra and Sodhi 2014; Ivanov et al. 2014b).

Companies which used single sourcing with suppliers in Japan or Thailand were drastically affected by the tsunami and floods in 2011. Many production factories worldwide were halted for several months. Intel claimed to have lost \$1 billion in sales during the fourth quarter of 2011. In 2010, the eruption of a volcano in Iceland interrupted many time-sensitive air shipments in global supply chains. A fire in the Phillips Semiconductor plant in Albuquerque, New Mexico in 2000 caused its major customer, Ericsson, to lose \$200 million in potential revenue. Nokia was also affected by this disruption, but was able to find an alternative supply source.

Online fashion retailer ASOS was badly affected by a fire in their UK warehouse in 2005 when operations were stopped for almost 1 month. They then developed a contingency policy for such disruptions. Among other solutions, an additional warehouse was established in Asia. This helped the company to recover within 2 days in June 2014 when a new fire occurred in the UK warehouse. Back-up information technology solutions are also typical redundancy strategies in practice.

A mixed strategy with a combination of local and global sourcing elements can be a good choice. For example, Amazon prefers holding fast-moving items in distribution centres while slow-moving items tend to be stored centrally. Apple localized production in China, but the distribution network is global. Such supply

Table 5.2 Methods for supply chain risk mitigation and recovery.

Flexibility	Redundancy	Organization
Dual or multiple sourcing (Yu et al. 2009; Yang et al. 2012; Sawik 2013)	Inventory (Bensoussan et al. 2007; Wilson 2007; Shu et al. 2010; Chen et al. 2011; Hsu and Li 2011; Carvalho et al. 2012; Kouvelis and Li 2012; Hishamuddin et al. 2013; Paul et al. 2014)	Supply chain risk management as a part of supply chain organization
Process and product flexibility (Graves and Tomlin 2003; Simchi-Levi and Wei 2015; Teimoury and Fathi 2013; Meisel and Bierwirth 2014)	Redundant capacities (Snyder and Daskin 2005; Goh et al. 2007; Wilson 2007; Azaron et al. 2008; Cui et al. 2010; Ivanov et al. 2010, 2013; Klibi et al. 2010; Qi et al. 2010; Baron et al. 2011; Peng et al. 2011; Lewis et al. 2013; Li et al. 2013a; Lim et al. 2013; Rafiei et al. 2013)	Contingency plans (Iakovou et al. 2010; Hu et al. 2013; Ivanov et al. 2013, 2014a, b)
Coordination strategies VMI и CPFR (Chen et al. 2000; Ouyang and Li 2010; Govindan 2015; Xu et al. 2015)	Back-up suppliers (Hou et al. 2010; Lim et al. 2010; Ravindran et al. 2010; Federgruen and Yang 2011; Schmitt and Singh 2012; Shao and Dong 2012; Benyoucef et al. 2013; Li et al. 2013a; Sawik 2013)	Collaborative information system
	Financial reserves	Early warning systems
	Information system back-up (Ivanov et al. 2014c)	Supply chain security standards

chain segmentation also helps to reduce disruption risk implications (Chopra and Sodhi 2014).

In addition, companies implement product and process flexibility extensively (see e.g., the new Volkswagen production system strategy). This includes process simplification and standardization as well as product modularization and postponement. Through the new production system, cost per vehicle should decrease by about €1500 (Volkswagnis 2012). This will be achieved through:

- introduction of flexible assembly lines, producing various models (e.g., the new VW plant in China can produce two different Golf models as well as two different Audi models on the same assembly line);
- standardization of production processes (e.g., one painting procedure for all 90 plants instead of 90 different ones as is now the case);
- a reduction in the number of variations (e.g., only 28 variations of air-conditioning instead of 102 as is now the case).

However, there are also risks related to product standardization. If the sole supplier produces items which are used in many different models of a product,

the impacts of a disaster can ripple very fast through the supply chain as in the case of Toyota in 2011. That is why many companies, such as Samsung, tend to have at least two suppliers even if the second one provides only 20% of the volume (Sodhi and Lee 2007).

A good example of the importance of the organizational issues in supply chain risk management is Nissan (Schmidt and Simchi-Levi 2013), which managed to recover quickly and efficiently after the disaster in 2011 in Japan. This area covers both establishing supply chain risk management as a function in an organization and creating collaborative information systems along with supply chain security standards.

5.7.3 *Application of Quantitative Analysis Methods*

Based on the literature analysis, our next objective is to derive some classifications regarding the following issues:

- What types of disruptive risks can be supported by quantitative methods?
- How can the supply chains be protected against operational risks and disruptions with the help of quantitative methods?
- How can quantitative tools be used to react to and develop recovery measures?
- Which quantitative methods are most suitable for certain problem in supply chain risk management and control?

Table 5.3 depicts the matrix “risks-recovery-methods” and provides a general overview of the usage of quantitative analysis methods in different areas of operational and disruption risks in supply chains. The range from “*****” (very high) to “*” (very low) depicts the number of research studies in different areas. We note that Table 5.3 shows the overall trends in quantitative research on operational and disruption risks in supply chains and does not pretend to be a full collection of the published papers on these topics.

In addition, we summarize the applications of quantitative methods in the “risks-measures” matrix (see Table 5.4) in order to depict with “x” the areas where quantitative research is typically applied.

It can be observed from Tables 5.3 and 5.4 that the literature analyzed considers five basic types of risks that should be addressed by supply chain managers:

- demand and supply operational risks
- production and transportation disruptions, especially in global supply chains
- product-related disruption risks due to a high degree of supplier specialization
- information flow disruptions
- disruptions in financial flows.

Next, recent literature has focused on different recovery strategies. Six elements of proactive supply chain protection are classified:

Table 5.3 Matrix “risks-recovery-methods”

		Proactive planning				Reactive planning			
		Math. opt.	Stoch./ rob. opt.	Simulation/ control theory	Game theory.	Math. opt.	Stoch./ rob. opt.	Simulation and control theory	Game theory
Risk sources	Demand	**	****	***	***	*	*	****	**
	Supply	*	*	***	**		*	*	*
	Infrastructure	*****	***	***	*	*	***	***	
		***		***	*		**	**	*
		*	***	**	***		**	**	****
Recovery/con-tingency measures	Flexibility		*		**		*	*	*
		*		***				*	
Redundancy	Flexible production processes								
	Inventory	*****	**	***	***	*		****	****
	Capacity	*****		**			**	**	*
	Back-up suppliers	***	**		**	*		**	**

(continued)

Table 5.4 Applications of quantitative research to different risks and recovery measures

		Flexibility			Redundancy			Organization					supply chain security standards	
		Dual or multiple sourcing	Flexible production processes	Coordination systems	Inventory	Buffer capacities	Back-up suppliers	Cash reserves	Information protection	Risk management organization	Contingency plans	IT for collaborations		
Operational risks	Demand	Demand volatility	×	×	×	×	×	×			×			
		Product variety		×		×			×					
		Information distortion			×									
	Supply	Order quantity and lead-time volatility	×	×	×	×	×	×			×			
		New product delays	×	×	×	×	×							
	Product	Quality problems with end products /product recalls		×		×	×							
Quality problems with raw materials		×			×		×							
Change in bill-of-materials		×	×	×	×		×							
	Regulations	Environmental regulations												
		Trade and customs regulations												
		Thefts and damages												
		Demand disruption		×										
Disruption risks	Supplier and logistics service	Supplier and logistics service												

(continued)

Table 5.4 (continued)

- back-up suppliers, depots and transportation channels
- inventory and capacity buffers
- supply chain localization and segmentation
- product and process flexibility
- coordination and contracting
- back-up information technology.

The reaction to disruptive events can be performed in five basic ways depending on the severity of disruptions:

- parametrical adaptation
- process and product adaptation
- structure adaptation
- system adaptation.

Parametrical adaptation represents the simplest case where stabilization and recovery are possible through the tuning of some critical parameters like lead-time or inventory. Process and product adaptation refer to flexibility reserves. Structure adaptation considers back-up suppliers or contingency transportation plans. System adaptation is the highest level of adaptation where strategy and organization have to be recovered.

5.7.4 Critical Analysis and Future Research Needs

With the help of optimization and simulation approaches, current research generates new knowledge to influence disruption propagation on the performance of supply chain outputs with consideration for disruption location, duration, propagation and recovery policies (Dolgui et al. 2018).

Despite mixed-integer programming, models provide interesting managerial insights and can be successfully used in cases where disruption probabilities can be fairly estimated; most of the mixed-integer programming solutions suggest opening new facilities. That increases total costs even if transportation costs are not increased. However, as pointed out in recent articles by Chopra and Sodhi (2014) and Simchi-Levi et al. (2014) it is almost impossible to determine the probability of factory fires, natural disasters or piracy in certain regions. This is why one has to concentrate mostly on mitigation strategies and identification of the impact of disruption on financial and operational performance, regardless of what caused the disruption.

In addition, a general shortcoming of existing studies, as pointed out by Cui et al. (2010) and Li et al. (2013a) is that the dynamics of supply chain execution is not considered. Disruptions are usually considered static events, without taking into account their duration, or what the stabilization/ recovery policies are.

Similar to mixed-integer programming, the assumptions of known reliability of suppliers and parametric probabilities make the stochastic programming models

generally difficult to handle and implement. In addition, a scenario-based approach exponentially increases the number of variables and constraints in stochastic formulations. For some practical challenges and solutions in this direction, we refer to van Delft and Vial (2004).

Generally, the application of fuzzy and robust optimization is related mostly to operational risks (e.g., demand fluctuations) and the tactical planning level with some episodic interfaces to supply chain design. The same can be stated for control models. In addition, as a general shortcoming of robust optimization, the tendency toward pessimistic solutions must be pointed out. In practice, it is hard to assume that managers will accept supply chain designs with low efficiency and high fixed costs only in anticipation of a worst case scenario.

Summarizing, investment in supply chain protection can help to avoid many problems with disruptive events. However, it is impossible to avoid disruption completely. Simchi-Levi et al. (2014) and Ambulkar et al. (2015) emphasize that focus should be directed toward recovery policies, regardless of what caused the disruption. Therefore, adaptation is needed to change supply chain plans, schedules or inventory policies in order to achieve the desired output performance. In this setting, supply chains can be robust and stable only on the basis of decisions that are taken by *people* (unlike a pendulum, which returns to the stable state due to natural laws, without adaptation). In supply chains, the *adaptation* (and more precisely, human-driven coordinated adaptation) is the precondition of stability and robustness (Ivanov and Sokolov 2013).

Management science and operations research along with system dynamics and control theory contain a number of useful methods that can be used for analysis and for mitigating the ripple effect. Different methods are suited to different problems. No single technique is likely to prove a panacea in this field. While mathematical and stochastic optimization has its place in supply chain design and planning stages without recovery considerations, they fail to throw much light on the dynamic behavior of the supply chain. The implications of strategic supply chain design and tactical plans on supply chain performance at the execution and recovery stages can be enhanced by using models based on the dynamics of the execution processes.

Reactive approaches can be based either on purely recovery policies without any supply chain proactive protection, or integrated in or with proactive approaches. We focus on the second case. Many proactive techniques include reactive elements. Mixed-integer programming formulations with facility fortification consider product shift to back-up suppliers if primary suppliers are disrupted. Model predictive control models implement a rolling, planning policy and explicitly include re-planning elements. Inventory control models also suggest policies for recovery. Simulation techniques consider “what-if” scenarios, which can be used by supply chain managers in the case of a disruption to quickly estimate the recovery policies and the impacts on operational and financial performance.

It is natural to use simulation to further study disruption propagations and the ripple effect in the supply chain. The existing studies considered time and length of disruptions and recovery policies. In the future, a sensitivity analysis of output supply chain performance, in regard to both parametrical and structural resilience

levers (i.e., different capacity levels, inventory control policies, dual sourcing and back-up facilities), needs to be performed. Such an analysis would show and substantiating major proactive and reactive decision-making support processes and models in regard to disruption severity, recovery policies and resilience levers in light of their singular and combinatorial performance impacts with consideration of disruption propagation in the supply chain. The expected results of research in this area are to provide new insights on how to estimate the impact of possible disruptions on performance in the pro-active stage, to estimate the impact of real disruptions on performance at the execution stage and to generate efficient and effective stabilization and recovery measures.

The main challenge in this domain is to extend resilience strategies which provide adequate protection from disruptions without reducing supply chain effectiveness in business-as-usual situations. The costs of adaptation should also be considered along with the costs of redundancy creation. It is observed that research on reactive policies is much limited, as in the proactive domain. We regard this as a future research opportunity.

While discrete-event and optimization based simulation have their focus rather on supply chain re-engineering resilience principles such as redundancy and flexibility, agent-based modelling can be applied to a broader scope of supply chain resilience principles. These principles may include collaboration (trust and information sharing) and supply chain risk management culture (e.g., leadership and risk-averse behavior). In this setting, agent-based modelling might be a suitable method to enhance existing simulation impact on supply chain ripple effect research in regard to non-engineering supply chain resilience principles.

This is quite a natural simulation feature to visualize the processes which has not yet been extensively used in modelling the ripple effect in the supply chain. In this regard, simulation models can enhance existing tools on supply chain agility and visibility in regard to disruption velocity.

The expected managerial results of ripple effect analysis in the supply chain are to provide new insights on the following questions:

- When does one failure trigger an adjacent set of failures?
- Which supply chain structures are particularly sensitive to the ripple/domino effect?
- What are typical ripple effect scenarios and what is the most efficient way to react in each of these scenarios?

In light of these reflections, a few directions for simulation application to ripple effect modelling in the supply chain can be derived. The possibility to change parameters dynamically during the experiment and observe the performance impact of these changes in real-time would close some research gaps, e.g.:

- consider disruption propagation in the supply chain;
- consider dynamic recovery policies;
- consider gradual capacity degradation and recovery;

- consider multiple performance impact dimensions including financial, service level, and operational performance.

Simulation analysis is of vital importance for supply chain operations planners and dispatchers at the tactical and operative decision-making levels, while optimization methods provide rigorous decision-making support for supply chain executives at the strategic level. By making changes to the simulated supply chain, one expects to gain understanding of the dynamics of the physical supply chain. Simulation is an ideal tool for further analyzing the performance of a proposed supply chain design derived from an optimization model. Simulation-based optimization can be considered, in this regard, as a technique that can integrate decision-making at strategic and tactical-operative levels.

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Chapter 6

Hybrid Multi-objective Mathematical Optimization: Optimal Control Model for Proactive Supply Chain Recovery Planning

6.1 Problem Statement and Modelling Approach

6.1.1 Management Problem Statement

We investigate a multi-stage supply chain that displays the following characteristics in line with recent studies (Amiri 2006; Manzini and Bindi 2009; Ivanov et al. 2014, 2015, 2016, 2017; Sawik 2016): (i) system performance depends on its ability to execute despite perturbations; (ii) some system elements may become unavailable because of disruptions in the supply chain, and (iii) the system experiences performance degradation if some of its elements fail.

The problem statement captures the following elements:

- Multi-stage, multi-product, multi-period supply chain planning;
- Network structure is dynamic, nodes and arc may become unavailable for different durations;
- Bill-of-materials and different processing intensities;
- Reconfiguration of material flows in the event of a disruption and computation of the performance impact of the disruption, taking into account optimal reconfiguration and recovery costs;
- Upstream supply control in the event of disruption subject to the total supply chain costs minimization;
- Different proactive actions: structural and parametrical;
- Sales volumes and service level as resilience indicators;
- Sourcing, transportation, processing, return, fixed, inventory and recovery costs are used for efficiency assessment and are assumed to be linear functions from the quantities;
- Multiple objective views: logistics (costs minimization), customer (service level), system (supply chain design and disruptions);

- Time duration of a disruption modelled as continuous time function in dynamic model;
- Impact of disruptions on the economic performance which is simulated using a hybrid static-dynamic optimization model.

Transportation volumes are constrained by maximal transportation intensity. Inventory volume is constrained by maximal warehouse capacities. Processing at terminals and hubs is constrained subject to maximal in- and outbound processing intensities. Suppliers deliver certain order quantities at the beginning of each period, and many periods are involved in the planning horizon. It is assumed, that:

- capacities and order quantities are variable and represented as time functions;
- the demands of the regional distribution center may change in each period;
- any node or arc in the network may be temporarily unavailable;
- an inventory from previous periods may be used in the following periods;
- if processing and warehouse capacity is exceeded by the delivered quantity, unprocessed and non-stored goods are sent back to an additional warehouse (not in the main network) subject to additional return costs;
- delivered and received product flows may be different (e.g., due to debts/damage during the transportation).

The primary problem is to find the aggregate product flows to be moved from suppliers through the intermediate stages to the strategic inventory holding point, subject to maximizing the service level and minimizing the total cost under (i) constrained capacities and processing rates and (ii) varying demand, supply and supply chain structure for a multi-period case. In addition, the calculated plans should suggest ways for reconfiguring product flows in the case of structure dynamics and severe disruptions. The performance impact of disruptions with consideration of material flow reconfiguration should be computed and disruption and recovery time and costs should be taken into account.

6.1.2 Modelling Approach

We implement a hybrid modelling approach that combines elements of mathematical programming and optimal control theory (Ivanov and Sokolov 2010; Ivanov et al. 2014). Mathematical programming is applied to formulate a static optimization model. The optimal control model describes supply chain structural dynamics in detail.

The features of the proposed approach are as follows. First, a dynamic optimal program control model is formulated to show the problem statement in the non-stationary, continuous-time mode. This model is interconnected with the execution scenarios and is needed to describe the structure dynamics control. Because the dynamic control model contains piecewise functions in the right

parts differential equations to describe the structure dynamics, the calculation procedure in this model is complicated both theoretically and practically.

Subsequently, it is assumed that although supply chain structure and parameters may change the non-stationary mode, these changes are not constant, and there are intervals of structural constancy. For these intervals, a multi-objective linear programming model with transit nodes and two side constraints is formulated. The practical logic of decision-making in companies is therefore taken into account. Economic order quantities are calculated based on predicted demand. This is why there is no need to include a demand constraint into the model formulation again. The exclusion of the demand constraint allows transit from classical linear programming to a maximal flow problem, which is formulated as a linear programming model. This has two advantages. First, the economic requirement on increasing service level is addressed. Second, the dual model can be easily formulated.

6.2 Mathematical Model

6.2.1 Problem Description

Consider a multi stage supply chain that comprises a set $A = \{A_{i,j}\}$, $i, j \in M = \{1, \dots, m\}$ of companies, where M is the total number of companies in the supply chain. Supply chain structure changes at each l -time interval, $l \in L = \{1, \dots, k\}$, where L is the total number of intervals of structural constancy. Processing and storage are limited subject to maximal processing and storage capacities V_{jl} and ψ_{ijl} , respectively. The problem comprises the determination of shipment, processing and storage quantities subject to the highest possible service level and minimum possible total costs in the supply chain. Service level is measured as the quantity actually delivered within lead time compared to planned delivery quantity. Total costs comprise processing, holding, shipment and return costs (Ivanov et al. 2014, 2016, 2017).

The following decision variables are needed for problem formalization: the amount x_{ijl} of products transmitted from A_i to A_j (i.e., the transportation plan) at structural constancy interval number l ; product amounts y_{jl} , g_{jl} , z_{ijl} and relating to the node A_j and respectively to be stored (either planned or due to an unavailability of processing capacities), to be processed (i.e., lot-sizes), and to be delayed (as caused by limited capacity of supply chain nodes and channels). Let q_{jl}^+ and q_{jl}^- be the set of node numbers for the nodes transmitting and receiving products at time interval l respectively.

6.2.2 Linear Programming Model

The linear programming model, i.e. the aggregate supply chain planning within each of the l -subintervals can be stated as Eqs. (6.1), (6.2), and (6.3).

$$\alpha_1 \sum_{j=1}^m \sum_{l=1}^k g_{jl} - \alpha_2 \sum_{j=1}^m \sum_{l=1}^k z_{jl} = I \rightarrow \max, \quad (6.1)$$

$$x_{jl} = \sum_{i \in Q_{jl}^{(-)}} x_{ijl} - \sum_{i \in Q_{jl}^{(+)}} x_{ijl} + (y_{j(l+1)} - y_{jl}) + z_{jl} + g_{jl}, \quad (6.2)$$

$$0 \leq x_{ijl} \leq \psi_{ijl}; \quad 0 \leq x_{jl} \leq V_{jl}; \quad 0 \leq g_{jl} \leq \phi_{jl}; \quad z_{jl} \geq 0 \quad (6.3)$$

The planning problem (6.1), (6.2), and (6.3) is a multi-objective linear programming problem of high dimensionality. Equation (6.1) characterizes both the amount of the products processed at the l -interval and the amount of delayed products at the same time interval. The dimensionality could become significantly larger if different types of products, intensity-dependent costs of production and transportation and time intervals would be included in the model. This is why we will consider these parameters in the dynamic model. Constraint (6.2) reflects that the number of products x_{jl} delivered to the node A_j at the time interval l can be transmitted to other nodes, or processed and storage at this node, or delayed. The required program of supply chain operation should provide the maximal value for the generalized objective function I that reflects the supply chain *service level*. Here the first component $I_1 = \alpha_1 \sum_{j=1}^m \sum_{l=1}^k g_{jl}$ of objective function (6.1) characterizes the total amount of customer orders processed in the supply chain and the second component $I_2 = \alpha_2 \sum_{j=1}^m \sum_{l=1}^k z_{jl}$ characterizes the amount of customer orders not fulfilled. Both I_1 and I_2 refer to the supply chain service level. For the case of *cost minimization*, an additional objective function may be introduced under the assumption of linear costs behavior. The multi-objective resolution can be performed in this case based on the *priority coefficients* α . The result of the static linear programming model is the aggregate supply chain planning that now needs to be set in detail with the help of a dynamic control model.

6.2.3 Optimal Control Model

In this section, we show the linear programming model with the help of an optimal program control-based dynamic model to describe structural and parametrical dynamics. This description is necessary since special consideration must be given to the fact that real supply chains operate with heterogeneous products of different

importance and priority of customer orders. Besides, intensity-dependent transportation capacities, costs, etc., as well as time-dependent perturbations, should be considered.

6.2.3.1 Mathematical Model

We propose describing supply chain planning (in the terms of model (6.1), (6.2), and (6.3)) via the following deterministic *dynamic model* for different products ρ (6.4):

$$\begin{aligned} x_l^{(a,1)} &= u_l^{(a,1)}; \quad x_{ij\rho l}^{(n,1)} = u_{ij\rho l}^{(n,1)}; \quad x_{j\rho l}^{(n,2)} = u_{j\rho l}^{(n,2)}; \quad x_{ij\rho l}^{(n,3)} = \omega_{ij\rho l}^{(n,1)}; \\ x_{j\rho l}^{(n,4)} &= \omega_{j\rho l}^{(n,1)}; \quad x_{\rho l}^{(n,5)} = \omega_{\rho l}^{(n,5)} \quad i, j, \tilde{j} \in \{1, \dots, m\}, \end{aligned} \quad (6.4)$$

where

- $x_l^{(a,1)}$ are auxiliary variables which characterize the duration of the time interval l ;
- $x_{ij\rho l}^{(n,1)}$ is an amount of product ρ transmitted from A_i to A_j on the time interval l ;
- $x_{j\rho l}^{(n,2)}$ is an amount of ρ -type product processed at $A_{\tilde{j}}$ within the time interval l ;
- $u_{ij\rho l}^{(n,1)}(t)$ is a transportation intensity in the channel $A_i \rightarrow A_j$;
- $u_{j\rho l}^{(n,2)}(t)$ is a processing intensity at the node $A_{\tilde{j}}$;
- $x_{ij\rho l}^{(n,3)}$, $x_{j\rho l}^{(n,4)}$ and $x_{\rho l}^{(n,5)}$ are auxiliary variables denoting the time passed from the beginning of product transportation in the channel $A_i \rightarrow A_j$, the time passed from the beginning of product processing or product storage, and the time passed from the completion of product processing to the end of planning horizon t_l respectively (for the node $A_{\tilde{j}}$, the interval l , and the information of the type ρ),
- $\omega_{ij\rho l}^{(n,3)}(t)$ and $\omega_{j\rho l}^{(n,4)}(t)$ are 0–1 auxiliary binary control variables subject to the decision on transportation or processing at time t , and
- $\omega_{\rho l}^{(n,5)}(t)$ 0–1 auxiliary binary control variables subject to the completion of the processing in the node A_i .

6.2.3.2 Constraints

The control and state variables should meet the *constraints* on maximal intensities and capacities of transportation and processing $c_{ij\rho l}^{(n,1)}$, $c_{j\rho l}^{(n,2)}$ and $d_{ij\rho l}^{(n,1)}$, $d_{j\rho l}^{(n,2)}$. These constraints now have dynamic form and use in the right parts of inequalities, the values of $x_{ij\rho l}$ and $g_{j\rho l}$ found in the static model. In addition, the functions $\xi_{ij}^{(1)}$, $\xi_j^{(2)}$ define possible perturbations during the transportation execution so that $0 \leq \xi_{ij}^{(1)}$

≤ 1 and $0 \leq \xi_j^{(2)} \leq 1$ (see Eqs. (6.5), (6.6), (6.7), (6.8), (6.9), (6.10), (6.11), (6.12), (6.13), and (6.14)).

$$u_{(l+1)}^{(a,1)}(t) \left(a_l - x_l^{(a,1)}(t) \right) = 0; \quad l = 1, 2, \dots, L; \quad (6.5)$$

$$0 \leq u_{ij\phi l}^{(n,1)}(t) \leq c_{ij\phi l}^{(n,1)} \omega_{ij\phi l}^{(n,1)}; \quad i = 1, \dots, n \quad (6.6)$$

$$0 \leq u_{j\phi l}^{(n,2)}(t) \leq c_{j\phi l}^{(n,2)} \omega_{j\phi l}^{(n,2)}; \quad j = 1, \dots, m; \quad (6.7)$$

$$\sum_{\rho=1}^P \int_{t_l=t_{0l}}^{t_{l+1}=t_{fl}} u_{ij\phi l}^{(n,1)}(\tau) d\tau = x_{ijl}; \quad l = 1, \dots, L; \quad (6.8)$$

$$\sum_{\rho=1}^P \int_{t_l}^{t_{l+1}} u_{j\phi l}^{(n,2)}(\tau) d\tau = g_{jl}; \quad l = 1, \dots, L; \quad (6.9)$$

$$\sum_{i=1}^n \omega_{ij\phi l}^{(n,1)}(t) + \omega_{j\phi l}^{(n,2)}(t) \leq 1; \quad \forall l; \forall j; \forall \rho; \quad (6.10)$$

$j \neq i$

$$\sum_{\rho=1}^P u_{ij\phi l}^{(n,1)}(t) \leq d_{ijl}^{(1)}; \quad \sum_{\rho=1}^P u_{j\phi l}^{(n,2)}(t) \leq d_{jl}^{(2)}; \quad (6.11)$$

$$d_{ijl}^{(1)} = \xi_{ij}^{(1)} \sum_{\rho=1}^P c_{ij\phi l}^{(n,1)}(t); \quad d_{jl}^{(2)} = \xi_j^{(2)} \sum_{\rho=1}^P c_{j\phi l}^{(n,2)}(t); \quad (6.12)$$

$$\omega_{\rho l}^{(n,5)} \left(a_{\rho l}^{(n,2)} - \sum_{j=1}^m x_{j\phi l}^{(n,2)}(t_{fl}) \right) = 0; \quad (6.13)$$

$$\omega_{ij\phi l}^{(n,1)}(t), \omega_{j\phi l}^{(n,2)}(t), \omega_{\rho l}^{(n,5)}(t) \in \{0, 1\}. \quad (6.14)$$

Constraints (6.5) specify an arranged sequence of time intervals of supply chain structural constancy. $a_{(l+1)}$ is a given duration of the interval of structural constancy $(l+1)$ according to the static model. In optimal program control, time becomes an independent variable which exists in a model implicitly and does not influence problem dimensionality. Equations (6.6) and (6.7) specify the limits for the intensity of product transportation and processing ($c_{ij\phi l}^{(n,1)}(t)$, $c_{j\phi l}^{(n,2)}$ are given constants).

Constraints (6.8) and (6.9) are isoperimetric constraints on integral transportation capacity. Note that the values of x_{ijl} and g_{jl} have been found in the static model. Constraints (6.10) specify the rules for the operations of the node A_j , i.e. the ρ -type product is either transmitted to other nodes ($\omega_{ij\phi l}^{(n,1)}(t) = 1$), or is processed or stored in the same node ($\omega_{j\phi l}^{(n,2)}(t) = 1$). Inequalities (6.11) constrain processing capacity.

Possible capacity disruptions are considered in Eqs. (6.12). The continuous perturbation functions $\xi_{ij}^{(1)}$, $\xi_j^{(2)}$ define disruption scenarios in both transportation and facility capacity availability. We assume that $0 \leq \xi_{ij}^{(1)} \leq 1$ and $0 \leq \xi_j^{(2)} \leq 1$.

This implies that in the case of $\xi_{ij}^{(1)} = \xi_j^{(2)} = 1$, all capacities are available, and in the case of $\xi_{ij}^{(1)} = \xi_j^{(2)} = 0$, the supply chain is destroyed.

Constraints (6.13) define the logic for control. $\omega_{\rho l}^{(n,5)}(t)$. $\omega_{\rho l}^{(n,5)} \left(a_{\rho l}^{(n,2)} - \sum_{j=1}^m x_{j\rho l}^{(n,2)}(t_{fl}) \right) = 0$ holds if the order processing at the node A_j is completed. Constraints (6.14) determine the range of feasible values for variables $\omega_{ij\rho l}^{(n,1)}(t)$, $\omega_{j\rho l}^{(n,2)}(t)$, and $\omega_{\rho l}^{(n,5)}(t)$.

6.2.3.3 Boundary Conditions

Further, the border conditions should be set (Eqs. 6.15, 6.16, and 6.17):

$$x_l^{(o,1)}(t_{0l}) = x_{ij\rho l}^{(n,1)}(t_{0l}) = x_{j\rho l}^{(n,2)}(t_{0l}) = x_{ij\rho l}^{(n,3)}(t_{0l}) = x_{j\rho l}^{(n,4)}(t_{0l}) = x_{\rho l}^{(n,5)}(t_{0l}) = 0 \quad (6.15)$$

$$x_l^{(o,1)}(t_{fl}) = a_l^{(1)}; \quad \sum_{\rho=1}^P x_{ij\rho l}^{(n,1)}(t_{fl}) = x_{ijl}; \quad (6.16)$$

$$\sum_{\rho=1}^P x_{j\rho l}^{(n,2)}(t_{fl}) = g_{jl}; \quad \sum_{\rho=1}^P x_{j\rho l}^{(n,2)}(t_{fl}) = a_{\rho l}^{(n,2)} \quad (6.17)$$

Equations (6.15), (6.16), and (6.17) define the start and end conditions for the state variables in the vector $\mathbf{x}(t)$. In our case, it is to ensure that supply chain operations are executed fully, in other words, all the customer orders are completed by the end of the planning horizon.

6.2.3.4 Objective Functions

The *objectives* can be formulated as Eqs. (6.18), (6.19), (6.20), (6.21), (6.22), (6.23), and (6.24):

$$J_1 = \sum_{l=1}^L \sum_{\rho=1}^P \sum_{j=1}^m \int_{t_l}^{t_{l+1}} \gamma_{j\rho l}(\tau) \omega_{j\rho l}^{(n,2)}(\tau) d\tau; \quad (6.18)$$

$$J_2 = \sum_{l=1}^L \sum_{\rho=1}^P \sum_{j=1}^m \int_{t_l}^{t_{l+1}} \beta_{j\rho l}(\tau) \omega_{j\rho l}^{(n,2)}(\tau) d\tau; \quad (6.19)$$

$$J_3 = \frac{1}{2} \sum_{l=1}^L \left\{ \left[a_l^{(1)} - x_l^{(1)}(t_{fl}) \right]^2 + \sum_{\rho=1}^P \left[a_{\rho l}^{(n,2)} - \sum_{j=1}^m x_{j\rho l}^{(n,2)}(t_{fl}) \right]^2 \right\}; \quad (6.20)$$

$$J_4 = \frac{1}{2} \sum_{l=1}^L \left\{ \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^m \left[\left(x_{ijl} - \sum_{\rho=1}^P x_{ij\rho l}^{(n,1)}(t_{fl}) \right)^2 + \left(g_{jl} - \sum_{\rho=1}^P x_{i\rho l}^{(n,2)}(t_{fl}) \right)^2 \right] \right\}; \quad (6.21)$$

$$J_5 = \sum_{l=1}^L \sum_{\rho=1}^P \left\{ \sum_{\Delta=1}^{2n-1} \sum_{\Delta_1=\Delta+1}^{2n} \left[\int_{t_l}^{t_{l+1}} \left(x_{\Delta\rho l}^{(n,3)}(\tau) - x_{\Delta_1\rho l}^{(n,3)}(\tau) \right)^2 d\tau + \left(x_{\Delta\rho l}^{(n,3)}(t_{fl}) - x_{\Delta_1\rho l}^{(n,3)}(t_{fl}) \right)^2 \right] \right\}; \quad (6.22)$$

$$J_6 = \sum_{l=1}^L \sum_{\rho=1}^P \left\{ \sum_{\delta=1}^{2n-1} \sum_{\delta_1=\delta+1}^{2n} \left[\int_{t_l}^{t_{l+1}} \left(x_{\delta\rho l}^{(n,4)}(\tau) - x_{\delta_1\rho l}^{(n,4)}(\tau) \right)^2 d\tau + \left(x_{\delta\rho l}^{(n,4)}(t_{fl}) - x_{\delta_1\rho l}^{(n,4)}(t_{fl}) \right)^2 \right] \right\}; \quad (6.23)$$

$$J = \left(J^{(\min)} - J^{(\xi)} \right). \quad (6.24)$$

The objective functions express total delay and non-perfect fulfilment costs (Eqs. 6.18 and 6.19), the completeness of (6.20) and (6.21) subject to the Eqs. (6.16) and (6.17), and the uniformity of channel and node utilization in the supply chain (Eqs. 6.22 and 6.23). $\gamma_{j\rho l}(\tau)$ and $\beta_{j\rho l}(\tau)$ are given penalty cost functions. Performance indicator (6.24) is used for resilience analysis with the help of attainable sets (see Chap. 3). In Eq. (6.24), $J^{(\min)}$ are minimum values of the objective functions J_1 – J_6 , which are set up by managers. The real values of $J^{(\xi)}$ under disruptions are found while solving the described model.

6.3 Computational Procedure

6.3.1 Model Coordination

The coordination of the planning results of static model and dynamic model is carried out through the variables x_{ijk} , y_{jl} , and g_{jl} (aggregate amount of products) of the static model and the corresponding variables $x_{ijk}(t)$, $y_{jk}(t)$, and $g_{jk}(t)$ from the dynamic model, where vector $\mathbf{u}(\mathbf{t})$ is optimal program control vector, i.e., the optimal transportation plan. Besides, by considering different commodities and time intervals in the dynamic model, the dimensionality of the linear programming model can be reduced. By distributing elements between the static and dynamic model, the dimensionality of the linear programming model for the k -subintervals can be reduced, and non-stationarity of distribution processes and supply chain structure dynamics reflected. In addition, continuous representation may be useful for the processing industry which has continuous product flows.

Static models let us take into account the factors (losses, limitation of capacities) which define the state constraints in dynamic models. In addition, static models provide input data for the dynamic models while the direct enumeration of variants

is impracticable. In addition, static models take into account, to a first approximation, the structure dynamics in a supply chain and provide quantitative estimations for the amounts of stored, processed, and delivered products. However, the detailed, time-referenced description of product distribution and production is difficult within the static model. This is why we proposed to use the dynamic model of supply chain operation. Dynamic models let establish and optimize supply chain performance indicators that are difficult to express within a static model. Besides, dynamic models let use the advanced methods of the optimal program control theory for a synthesis of control programs as applied to supply chains.

6.3.2 Linear Programming Model Solution and Complexity

The developed model is a linear programming model with transit nodes and two-side constraints, it can be solved with the simplex method with consecutive plan improvement techniques implemented in any linear programming solver. The model includes $m \times k$ equations and $\left(\sum_{l=1}^k f_l + 3 \times m \times k \right)$ unknown variables, where f_l is the number of variables characterizing amounts of received (transmitted) products at the l -interval. Since the modified simplex method is used in the computational procedure, we avoid extensive numerical experiments. However, we note that the computational complexity increases subject to the number of different types of products and intensity-dependent costs of production and transportation.

Complexity of the linear programming problem can be estimated according to the complexity of the simplex method which can be used to solve the above-mentioned linear programming problem. This complexity can be estimated for one iteration as $O\left((\tilde{n} \cdot \bar{s} \cdot n)^2 + \tilde{n} \cdot \bar{s} \cdot n^2\right)$, where $\tilde{n}$ is the maximal number of customer orders processed or delivered in parallel within the planning interval, $\bar{s}$ is the average product number in orders, and n is the maximal number of parallel working resources in the supply chain. The complexity of the linear programming calculation can be estimated as shown in Eq. (6.25).

$$O\left((\tilde{n} \cdot \bar{s} \cdot n)^2 + \tilde{n} \cdot \bar{s} \cdot n^2\right) \cdot \left(\frac{\sigma}{\Delta t}\right) \quad (6.25)$$

6.3.3 Optimal Control Problem Solution

6.3.3.1 Hamiltonian Formulation

The *supply chain planning problem* can be now formulated as the following optimal program control problem: this is necessary to find a feasible control $\mathbf{u}(t)$, $(t_l, t_{l+1}]$, $l = 1, \dots, L$ that ensures the model (6.4) meets the vector constraint functions (6.5), (6.6), (6.7), (6.8), (6.9), (6.10), (6.11), (6.12), (6.13), and (6.14), and guides the dynamic system (i.e., the supply chain) $\mathbf{x}(t, \mathbf{x}, \mathbf{u})$ from the initial state (6.15) and (6.16) to the specified final state (6.17). If there are several feasible controls (schedules), then the best one (optimal) should be selected to maximize (minimize) a general performance indicator J_G (Ivanov et al. 2015):

$$J_G = \sum_{s=1}^S \alpha_s J_s; \quad \sum_{s=1}^S \alpha_s = 1, \quad (6.26)$$

where S is total number of weight coefficients.

In terms of control theory, the optimal program control of supply chain execution is at the same time the optimal distribution plan.

The stated optimal program control problem belongs to the class of non-classical problems of calculus of variations and can be transformed to the two-boundary problem with the help of the maximum principle. This requires construction of the Hamiltonian and conjunctive equation system. Then, transversality conditions for the conjunctive system must be found. They facilitate the link end conditions of the main (6.15), (6.16), and (6.17) and conjunctive equation systems.

The following Hamiltonian function is considered:

$$H(\mathbf{x}(t), \boldsymbol{\eta}(t), \mathbf{u}(t), t) = (H_1 + H_2 + H_3 + H_4 + H_5) \rightarrow \max_{\mathbf{u} \in Q}, \quad (6.27)$$

where Q is the admissible control area defined by Eqs. (6.5), (6.6), (6.7), (6.8), (6.9), (6.10), (6.11), (6.12), (6.13), and (6.14) and $\boldsymbol{\eta}(t)$ is the conjunctive vector.

The Hamiltonian (6.27) comprises five functions. Let us consider them in detail.

Hamiltonian H_1 :

$$H_1 = \sum_{l=1}^L \eta_l^{(0,1)} u_l^{(0,1)}(t) \rightarrow \max; \quad (6.28)$$

$$0 \leq u_l^{(0,1)}(t) \leq 1; \quad (6.29)$$

$$u_l^{(0,1)}(a_l^{(0,1)} - x_l^{(0,1)}(t)) = 0. \quad (6.30)$$

Hamiltonian H_2

$$H_2 = \sum_{l=1}^L \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \sum_{\rho=1}^P \eta_{ij\rho l}^{(n,1)} u_{ij\rho l}^{(n,1)}(t) \rightarrow \max; \quad (6.31)$$

$$0 \leq u_{ij\rho l}^{(n,1)}(t) \leq c_{ij\rho l}^{(n,1)} \omega_{ij\rho l}^{(n,1)}; \quad (6.32)$$

$$\sum_{\rho=1}^P u_{ij\rho l}^{(n,1)}(t) \leq d_{ijl}^{(1)}. \quad (6.33)$$

Hamiltonian H_3

$$H_3 = \sum_{l=1}^L \sum_{j=1}^n \sum_{\rho=1}^P \eta_{j\rho l}^{(n,2)} u_{j\rho l}^{(n,2)}(t) \rightarrow \max; \quad (6.34)$$

$$0 \leq u_{j\rho l}^{(n,2)}(t) \leq c_{j\rho l}^{(n,2)} \omega_{j\rho l}^{(n,2)}; \quad (6.35)$$

$$\sum_{\rho=1}^P u_{j\rho l}^{(n,2)}(t) \leq d_{jl}^{(2)}. \quad (6.36)$$

Hamiltonian H_4

$$H_4 = \sum_{l=1}^L \sum_{i=1}^n \sum_{j=1}^n \sum_{\rho=1}^P \left[\eta_{ij\rho l}^{(n,3)} \omega_{ij\rho l}^{(n,1)} + \eta_{j\rho l}^{(n,4)} \left(\gamma_{j\rho l}(t) + \beta_{j\rho l}(t) \omega_{j\rho l}^{(n,2)} \right) \right] \rightarrow \max; \quad (6.37)$$

$$\sum_{\substack{i=1 \\ j \neq i}}^n \omega_{ij\rho l}^{(n,1)}(t) + \omega_{j\rho l}^{(n,2)}(t) \leq 1; \quad \forall l; \forall j; \forall \rho; \quad (6.38)$$

$$0 \leq \omega_{ij\rho l}^{(n,1)}(t) \leq 1; \quad 0 \leq \omega_{j\rho l}^{(n,2)}(t) \leq 1. \quad (6.39)$$

Hamiltonian H_5

$$\sum_{l=1}^L \sum_{\rho=1}^P \eta_{\rho l}^{(n,5)} \omega_{\rho l}^{(n,5)} \rightarrow \max; \quad (6.40)$$

$$\omega_{\rho l}^{(n,5)} \left(a_{\rho l}^{(n,2)} - \sum_{j=1}^n x_{j\rho l}^{(n,2)}(t_{jl}) \right) = 0; \quad (6.41)$$

$$0 \leq \omega_{\rho l}^{(n,5)}(t) \leq 1. \quad (6.42)$$

The problem of Hamiltonian maximization is therefore deconstructed into the solution of two partial optimization problems:

- Assignment problem (H_1 , H_4 and H_5) where material flows are assigned to some arcs and nodes; and
- Linear programming problem where transportation and processing batches are defined (H_2 and H_3).

For the solution of the assignment and linear programming problem, standard computational software can be used.

6.3.3.2 Computational Algorithm, Transversality Conditions and Complexity Analysis

Step 1 An initial solution $\bar{\mathbf{u}}(t), t \in (T_{0l}, T_{fl}]$ (a feasible control, in other words, a feasible schedule regarding the model (6.4), (6.5), (6.6), (6.7), (6.8), (6.9), (6.10), (6.11), (6.12), (6.13), (6.14), (6.15), (6.16), and (6.17)) is selected, e.g., with the help of a dispatching rule, and $r = 0$.

Remark 1 At this step, we assume $\xi_j^{(1)}(t) = \xi_j^{(2)}(t) = 1, \forall t \in (t_{0l}, t_{fl}]$.

The initial solution can be formulated in two ways. The first option is the usage of a dispatching rule. The second option is to assume as feasible the plan $\bar{\mathbf{u}}(t) = 0$. In this case, at $t = t_{fl}$ we get the transversality conditions for $\mathbf{x}(t_{fl}) \equiv \mathbf{0}$ as follows:

$$\eta_l^{(0,1)}(t_{fl}) = \lambda_3 \left(a_l^{(0,1)} - x_l^{(0,1)}(t_{fl}) \right); \quad (6.43)$$

$$\eta_{ij\phi l}^{(n,1)}(t_{fl}) = \lambda_4 \left(x_{ijl} - \sum_{\rho=1}^P x_{ij\phi l}^{(n,1)}(t_{fl}) \right); \quad (6.44)$$

$$\eta_{j\phi l}^{(n,2)}(t_{fl}) = \lambda_3 \left(a_{\rho l}^{(n,2)} - \sum_{j=1}^n x_{j\phi l}^{(n,2)}(t_{fl}) \right) + \lambda_4 \left(g_{jl} - \sum_{\rho=1}^P x_{j\phi l}^{(n,2)}(t_{fl}) \right); \quad (6.45)$$

$$\eta_{\Delta \rho l}^{(n,3)}(t_{fl}) = -\lambda_5 \sum_{\Delta_1=\Delta+1}^{2n} \left(x_{\Delta \rho l}^{(n,3)}(t_{fl}) - x_{\Delta_1 \rho l}^{(n,3)}(t_{fl}) \right); \quad (6.46)$$

$$\eta_{\delta \rho l}^{(n,4)}(t_{fl}) = -\lambda_6 \sum_{\delta_1=\delta+1}^n \left(x_{\delta \rho l}^{(n,4)}(t_{fl}) - x_{\delta_1 \rho l}^{(n,4)}(t_{fl}) \right); \quad (6.47)$$

$$\eta_{\rho l}^{(n,5)}(t_{fl}) = 1. \quad (6.48)$$

subject to the *conjunctive system* (6.49), (6.50), (6.51), (6.52), and (6.53):

$$\eta_l^{(0,1)} = \eta_{l+1}^{(0,1)} u_{l+1}^{(0,1)}; \quad (6.49)$$

$$\eta_{ij\phi l}^{(n,1)} = 0; \quad \eta_{j\phi l}^{(n,2)} = 0 \quad (6.50)$$

$$\eta_{\Delta\phi l}^{(n,3)} = -\lambda_5 \sum_{\Delta_1=\Delta+1}^{2n} \left(x_{\Delta\phi l}^{(n,3)}(t) - x_{\Delta_1\phi l}^{(n,3)}(t) \right); \quad (6.51)$$

$$\eta_{\delta\phi l}^{(n,4)} = -\lambda_6 \sum_{\delta_1=\delta+1}^n \left(x_{\delta\phi l}^{(n,4)}(t) - x_{\delta_1\phi l}^{(n,4)}(t) \right); \quad (6.52)$$

$$\eta_{\rho l}^{(n,5)} = - \sum_{j=1}^n \eta_{j\phi l}^{(n,2)}(t) u_{j\phi l}^{(n,2)}(t). \quad (6.53)$$

The same *transversality conditions* are moved to the beginning of the planning interval. The values of the vector $\boldsymbol{\eta}_{o\phi}(t_{0l})$ at $t = t_{0l}$ are then defined as system (6.54), (6.55), (6.56), and (6.57):

$$\eta_l^{(o,1)}(t_{0l}) = \lambda_3 a_l^{(o,1)}; \quad (6.54)$$

$$\eta_{ij\phi l}^{(n,1)}(t_{0l}) = \lambda_4 x_{ijl}; \quad (6.55)$$

$$\eta_{j\phi l}^{(n,2)}(t_{0l}) = \lambda_3 a_{\phi l}^{(n,2)} + \lambda_4 g_{jl}; \quad (6.56)$$

$$\eta_{\Delta\phi l}^{(n,3)}(t_{0l}) = 1; \quad \eta_{\delta\phi l}^{(n,4)}(t_{0l}) = 1; \quad \eta_{\rho l}^{(n,5)}(t_{0l}) = 1 \quad (6.57)$$

At $t = t_{fl}$, the value of the general objective function J_G subject to Eqs. (6.18), (6.19), (6.20), (6.21), (6.22), (6.23), and (6.24) is calculated.

Remark 2 For simplification, it is assumed that the transition from the vector form $\mathbf{J}$ to a scalar form J_G has been performed on the basis of the weight coefficients for (6.18), (6.19), (6.20), (6.21), (6.22), (6.23), and (6.24). If there are several feasible controls (schedules), then the optimal one should be selected in order to maximize the components of J_G .

In the case of this option, go to step 4. Otherwise (if the first option is selected), continue with step 2.

Step 2 The main equation system (6.4), (6.5), (6.6), (6.7), (6.8), (6.9), (6.10), (6.11), (6.12), (6.13), (6.14), (6.15), and (6.17) is integrated with the initial conditions (6.15) and $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$ from $t = t_{0l}$ to $t = t_{fl}$. As a result of the dynamic model run, $\mathbf{x}^{(r)}(t)$ is received. Besides, if $t = T_f$ then the record value $J_G = J_G^{(r)}$ can be calculated. Then, the transversality conditions (6.44), (6.45), (6.46), (6.47), and (6.48) are evaluated.

Step 3 The conjugate system (6.49), (6.50), (6.51), (6.52), and (6.53) is integrated subject to $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$ and the transversality conditions (6.44), (6.45), (6.46), (6.47), and (6.48) and over the interval from $t = T_{fl}$ to $t = T_{0l}$. For the time $t = T_{0l}$, the first approximation $\boldsymbol{\eta}^{(r)}(t)$ is obtained as a result. Here, the iteration number $r = 0$ is completed.

Step 4 From the time point $t = T_0$ onwards, the control $\mathbf{u}^{(r+1)}(t)$ is determined ($r = 0, 1, 2, \dots$ denotes the number of the iteration). In parallel with the

maximization of the Hamiltonian, the main system of equations and the conjugate one are integrated. The maximization involves the solution of the assignment and linear programming problems (subject to H_1-H_5) at each time point. In the result, at $t = t_{\#}$ we get $\mathbf{x}^{(r)}(t_{\#})$, $\boldsymbol{\eta}^{(r)}(t_{\#})$, and $J_G = J_G^{(r)}(t_{\#})$.

The computational complexity of the proposed algorithm in one iteration is polynomial. With regard to the problem considered, the complexity of the proposed algorithm in one iteration is determined by the complexity of the assignment problem (H_1 , H_4 and H_5) and the linear programming problem (H_2 and H_3) in combination with respective constraints.

On the basis of the studies on the Hungarian method, the *complexity of the assignment problem* can be estimated according to Eq. (6.58)

$$O(\bar{m}_1^3) \left(\frac{\sigma}{\Delta t} \right), \quad (6.58)$$

where $\frac{O(\bar{m}_1^3)}{6} = 11\bar{m}_1^3 + 12\bar{m}_1^2 + 3\bar{m}_1$ is the maximal number of the “+” operations at one time point of the planning period $(T_o, T_f]$ for the assignment problem being solved via the Hungarian method; $\bar{m}_1$ is the maximal dimensionality of the assignment problem, i.e., the number of independent paths in the schedule execution network diagram, where σ is the duration of the planning interval; and Δt is the step length of integration for the main and the conjugate system. Note that the integration of the differential equations in the main and the conjugate system is not necessary due to their linearity. The computation can be performed subject to simple recurrent formulas.

Thus, the total complexity at one iteration is as follows in Eq. (6.59):

$$\bar{N} < \left[O(\bar{m}_1) + O\left((\tilde{n} \cdot \bar{s} \cdot n)^2 + \tilde{n} \cdot \bar{s} \cdot n^2 \right) \right] \cdot \left(\frac{\sigma}{\Delta t} \right), \quad (6.59)$$

where $\bar{N}$ is the average number of additional operations.

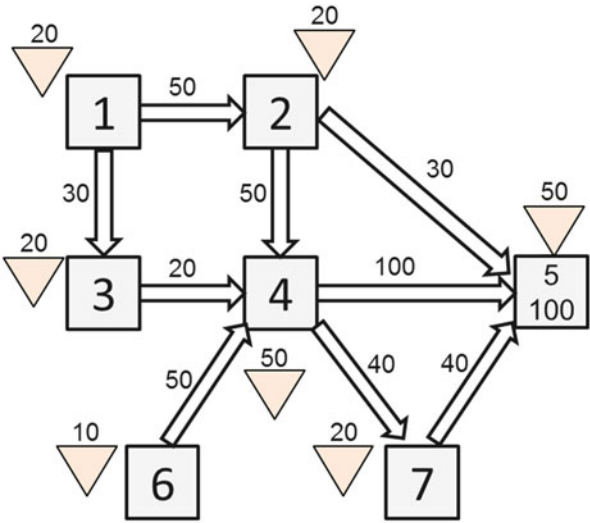
Since the complexity of the integer programming/linear programming problem at each cut is polynomial and the number of integration steps and iterations increases linearly, the computational complexity of the proposed algorithm is polynomial.

6.4 Experiments for Distribution Network Structural Dynamics

6.4.1 Supply Chain Design Structural Dynamics

Let us consider the following case-study. A distribution network of an enterprise in the FMCG (fast moving consumer goods) branch is considered (see Fig. 6.1).

Fig. 6.1 Distribution network structure



The distribution network is composed of two mega-hubs (nodes 1 and 6), a central distribution hub (node 4), two intermediate terminals (nodes 2 and 3), an outsourcing terminal (node 7), and a regional distribution center as the strategic inventory holding point (node 5). The execution in each of the nodes and transportation arcs is limited by maximal warehouse capacity, processing intensity, and transportation intensity, respectively (Ivanov et al. 2014).

The triangles refer to the warehouse capacity, and numbers on the arcs refer to maximal transportation intensity. The suppliers first deliver goods to the mega-hubs 1 and 6. Then, the goods will be processed in the central distribution hub 4. The goods from hub 1 are additionally processed at intermediate terminals 2 and 3. From hub 4, the goods are moved to the regional distribution center 5, which has a certain demand in each of the periods (i.e., 100 units). In practice, a number of the regional distribution centers are in the distribution network. Without loss of generality, we reduce this formulation in this paper to only one center. This is the centralized distribution network structure. As shown in previous studies (Tayur et al. 1999), the service level in such distribution network is measured (i) as the rate of the met demand and (ii) by closeness of the inventory to the customer, i.e., pushing the inventory to the strategic inventory holding point. In order to take into account possible problems with the channel 4→5, an outsourcing terminal is used as an alternative way for deliveries to reach the distribution center 5. Besides, it is possible to move small quantities (maximal 30 units) directly from terminal 2 to center 5. The problem is to maximize the service level under the assumption that demand will be 300 units for the planned period of 3 months (i.e., 100 units each month) while minimizing the costs from storage, transportation, return, sourcing and fixed costs. For simplification, processing costs and capacities are not considered in this example.

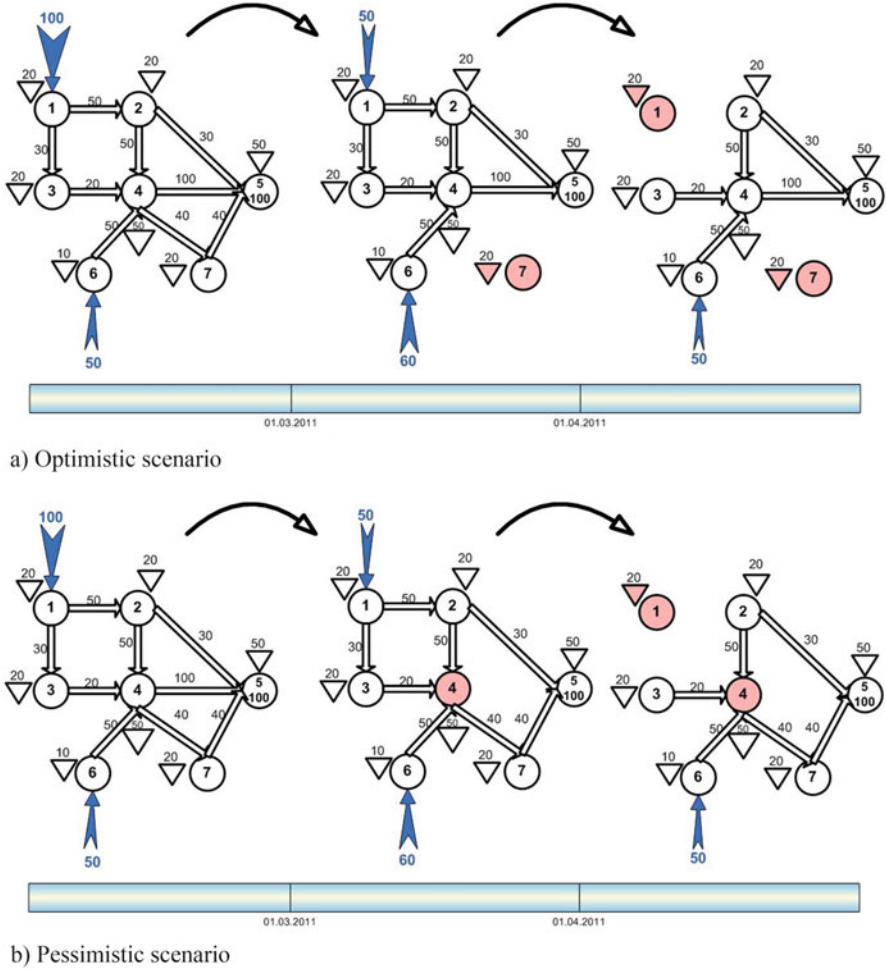


Fig. 6.2 Optimistic (*top*) and pessimistic (*bottom*) scenarios

Three intervals of structural constancy are considered subject to optimistic and pessimistic scenarios (see Fig. 6.2).

In the *optimistic trajectory*, the events for transition are the changes in sourcing volumes at nodes 1 and 6 as well as a failure in the operation of the terminal 7. Analogously, transition to the third interval of the structural constancy is launched by the failure in the operation of the mega-hub 1 and terminal 7 along with the change in sourcing volume in node 6. In the *pessimistic trajectory*, the transitions are triggered by the changes in sourcing volumes at nodes 1 and 6, as well as the unavailability of the link from the central distribution hub 4 to the regional distribution center 5. Analogously, transition to the third interval of the structural constancy is launched by failure in the operation of the mega-hub 1 and

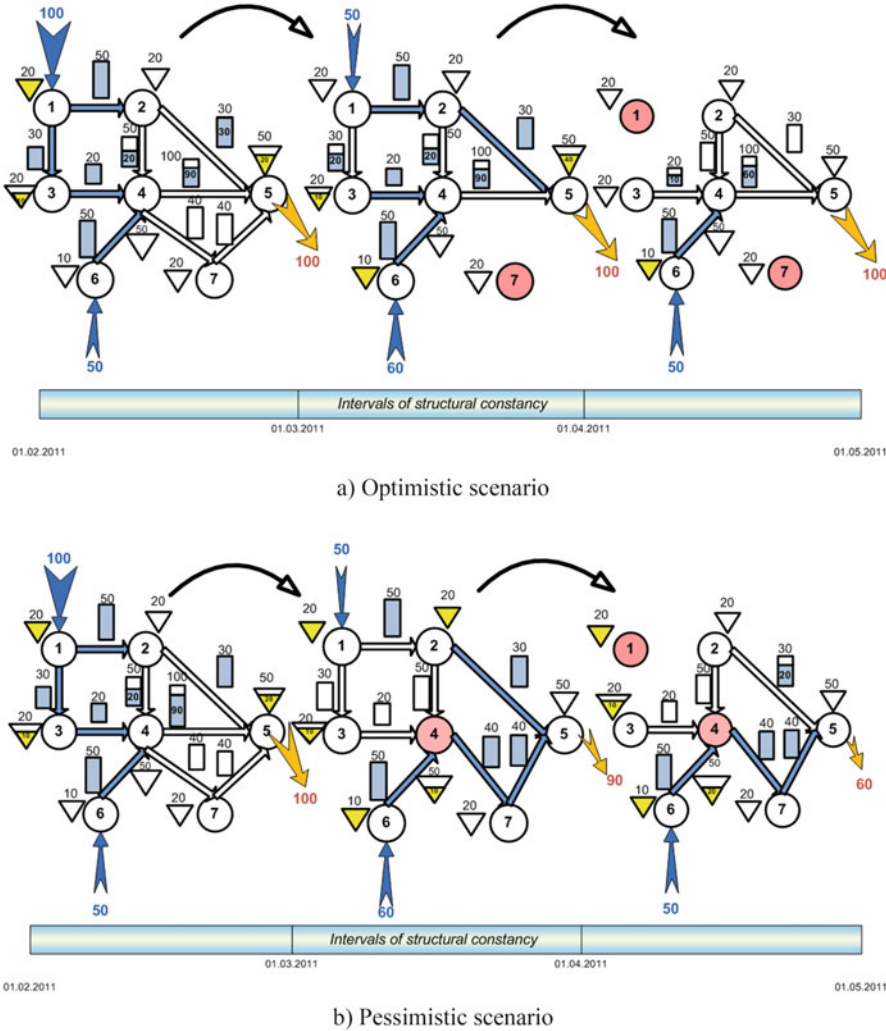


Fig. 6.3 Distribution plans for optimistic (*top*) and pessimistic (*bottom*) scenarios

further unavailability of the link from the central distribution hub 4 to the regional distribution center 5 along with a change in the sourcing volume in node 6.

6.4.2 Planning Results

In Fig. 6.3, results of optimal planning subject to the highest priority of the service level component in the objective function for the optimistic and pessimistic scenarios are presented.

Table 6.1 Planning results subject to key performance indicators

Performance indicator	Scenarios of structural dynamics control	
	Optimistic scenario	Pessimistic scenario
Volume of delivered goods	300.0	250.0
Volume of returned goods	0.0	0.0
Volume of inventory total	120.0	180.0
Volume of inventory at strategic inventory holding point	60.0	20.0
Transportation costs	28.6	27.0
Inventory costs	8.4	12.6
Fixed costs	90.0	90.0
Sourcing costs	124.0	124.0
Total costs	251.0	253.6
Total revenue	300.0	250.0
Profit	49.0	−3.6

The yellow triangles show the warehouse capacities and their actual utilization. The blue rectangles represent transportation channel capacities and the actual transportation quantities. By running the developed planning model on the assumption that the highest priority is service level in the goal function, the optimal solution for the optimistic scenario achieves delivery of 300 units, which is equal to a service level of 100%, subject to the planned demand of 300 units. Total inventory is 120 units with a distribution among periods as 50 units in the first period (caused by excessive sourcing quantities at nodes 1 and 6), 60 units in the second period, and 10 units in the third period.

Total cost and revenue have been calculated under the following assumptions: transportation cost per unit and per arc = 0.0415; inventory holding cost per unit and a period = 0.07; sourcing cost a unit = 0.4; return cost = 0.2; fixed costs for the distribution network = 90; and selling price = 1.0. Planning results subject to key performance indicators are presented in Table 6.1.

It can be observed that in the optimistic scenario, a profit of US\$49 can be achieved. For the pessimistic scenario, the optimal solution achieves delivery of 250 units, which is equal to a service level of 83.3%. Total inventory is 180 units with a distribution among periods as 50 units in the first period (caused by excessive sourcing quantities at nodes 1 and 6), 70 units in the second, and 60 units in the third period (caused mainly by the break in deliveries from 4 to 5). The operative reconfiguration in the second period is suggested as a reason for the increase in transportation intensities on the arcs $4 \rightarrow 7 \rightarrow 5$ and $2 \rightarrow 5$. The operative reconfiguration in the third period is suggested as a reason for the increase in transportation intensities on the arc $4 \rightarrow 7 \rightarrow 5$. It can be observed that in the pessimistic scenario, the selling volume decreases significantly and no profit can be achieved. The losses amount to US\$3.6.

6.4.3 Sensitivity Analysis

Further analysis may include two basic decision groups: (1) analysis of distribution plans in different scenarios of the distribution network structure dynamics subject to different disturbances; and (2) analysis of distribution network design excessiveness and flexibility subject to capacity and sourcing planning decisions. Let us concentrate on the analysis of the first group since the analysis of the second group requires the use of an inverse model that is not represented here.

Let us analyze the plans ($\delta_{optimistic}$, $\delta_{pessimistic}$) subject to the following disturbances:

- *variant 1* – decrease in transportation intensity on the way $4 \rightarrow 7 \rightarrow 5$,
- *variant 2* – decrease in warehouse capacity at the node 4,
- *variant 3* – decrease in transportation intensity on the way $4 \rightarrow 5$, and
- *variant 4* – influence of the variants (1)–(3) simultaneously.

6.4.3.1 Optimistic Scenario

Plan $\delta_{optimistic}$ was proved to be stable subject to the disturbances of variants 1 and 2. It can be observed from Fig. 6.3 that node 7 has not been selected for transportation and can actually be removed from the supply chain. The warehouse at node 4 has also not been used at all, and its capacity can be reduced significantly or eliminated (however, in the pessimistic scenario, this capacity can be used to adapt in the case of a disruption in the channel $4 \rightarrow 5$). In Fig. 6.4 analysis of the optimistic plan's sensitivity to the disturbance of the variant 3 is presented.

From Fig. 6.4 it can be observed that positive profits may be achieved by a transportation capacity decrease to 40 units. After this point, the revenue falls significantly. Similar a sensitivity analysis can be also performed for the pessimistic scenario subject to the disturbance No. 4.

Based on the sensitivity analysis for the optimistic and pessimistic scenarios it can be observed that:

- decrease in transportation intensity on the way $4 \rightarrow 5$ (disturbance no. 3) does not significantly influence the cost, but considerably impacts the volume of delivered goods in optimistic plan. On the other hand, the volume of delivered goods in pessimistic plan is influenced by the disturbance no. 3 only to a small extent.
- disturbance no. 1 influences the volume of the delivered goods only in the pessimistic scenario.
- decrease in warehouse capacity at node 4 (disturbance no. 2) does not influence the volume of the delivered goods neither in the pessimistic nor in the optimistic scenario. This is because of reserve warehouse capacities at other nodes in the distribution network.

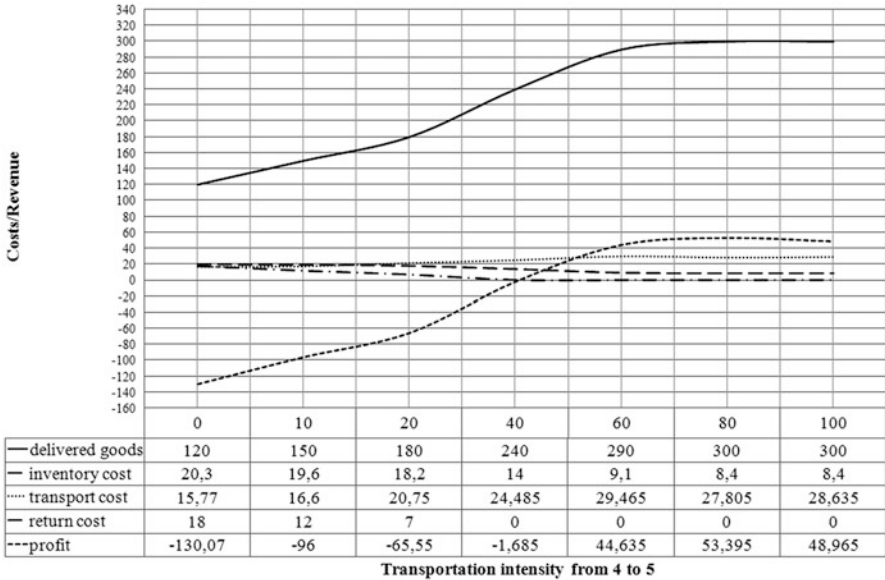


Fig. 6.4 Analysis of the optimistic plan’s sensitivity to the disturbance of the variant 3 (Ivanov et al. 2014)

6.4.3.2 Pessimistic Scenario

In Fig. 6.5, the results of the sensitivity analysis for the pessimistic scenario plan subject to the disturbances 1–4 are presented.

Corresponding cost and revenue based analysis can be performed analogously to the optimistic scenario as shown in Fig. 6.5. It can be observed that:

- decrease in transportation intensity on the way 4→5 (disturbance no. 3) does not significantly influence the cost, but considerably impacts the volume of delivered goods in the optimistic plan. On the contrary, the volume of delivered goods in the pessimistic plan is influenced by disturbance no. 3 only to a small extent.
- disturbance no. 1 influences the volume of the delivered goods only in the pessimistic scenario.
- decrease in warehouse capacity at node 4 (disturbance no. 2) does not influence the volume of the delivered goods neither in the pessimistic not in the optimistic scenario. This is because of reserve warehouse capacities at the other nodes in the distribution network,
- disturbances of variants 1 and 2 increase the volume of return flows to 15 and 20 units correspondingly. But their mutual impact (disturbance no. 4) increases the volume of return flows to 60 units (see Fig. 6.5).

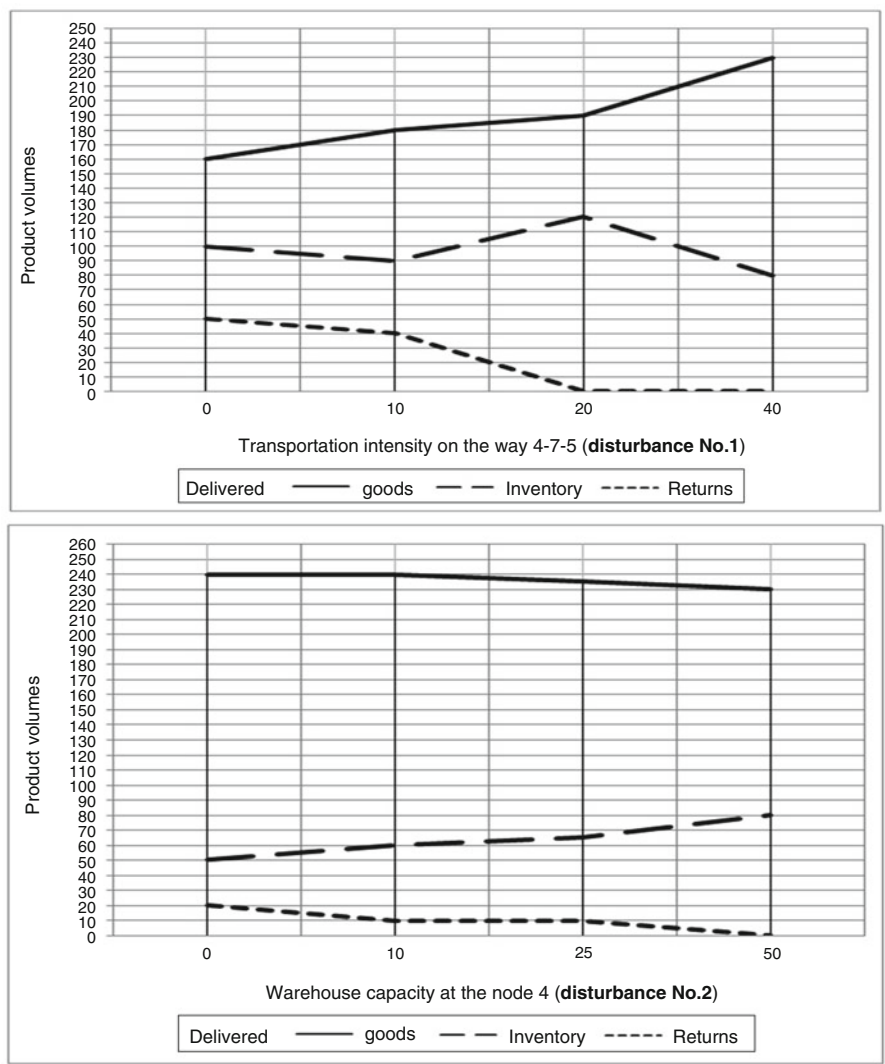


Fig. 6.5 Quantity-based analysis of the pessimistic plan’s sensitivity to the disturbances of the variants 1–4 (Ivanov et al. 2014)

6.4.4 Distribution Network Re-design

Further analysis may include two basic decision groups: (1) analysis of distribution plans in different scenarios of the distribution network structure dynamics, subject to different disturbances and (2) analysis of distribution network design

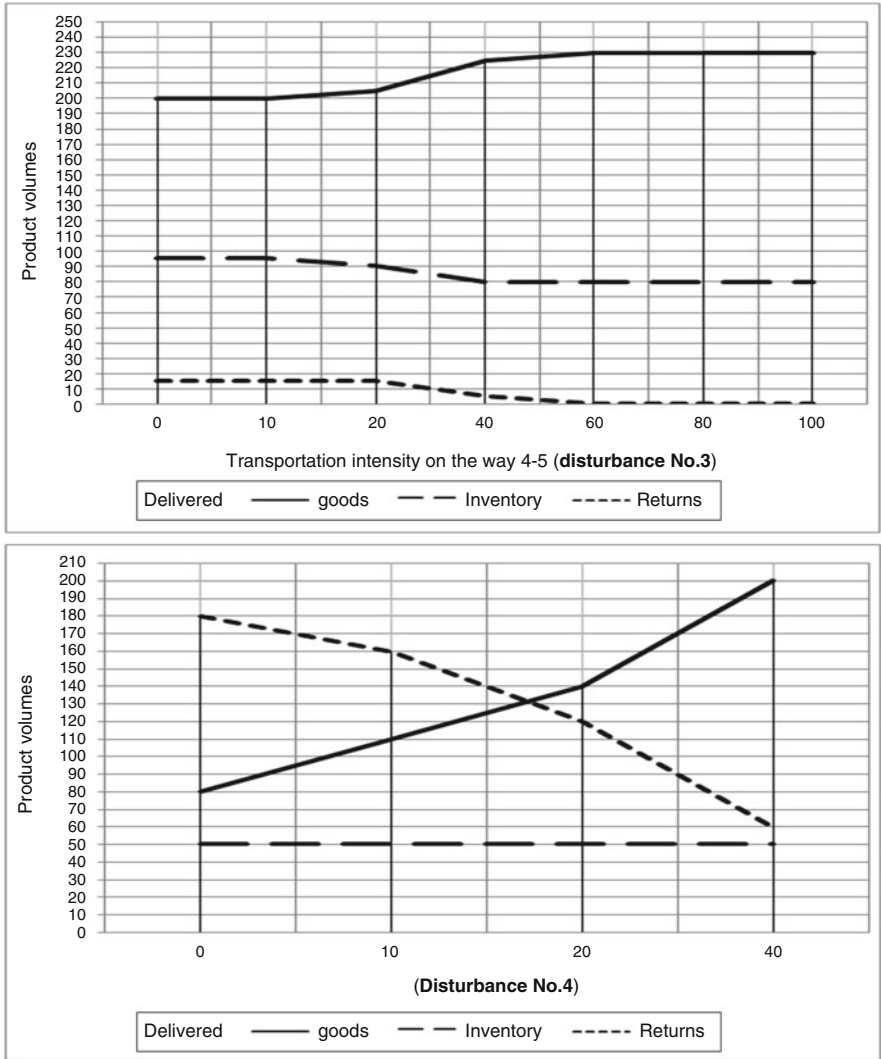


Fig. 6.5 (continued)

excessiveness and flexibility, subject to capacity and sourcing planning decisions. In particular, the following questions can be addressed:

- What elements are critical for supply chain design and what elements are excessive and can be removed without decreasing the service level?

- Do additional costs in supply chain design elements pay off by the increase in the service level, subject to mitigating the negative effects of possible operation failures or a large delivery flow volume?
- What sourcing quantities can be recommended for different scenarios?

For analysis of these questions, dual problem formulation will be applied. We refer for this formulation to the study (Ivanov et al. 2013). Dual problem formulation is a practical need in at least two cases. First, in the case of unsatisfied demand (i.e., no feasible linear programming solution), the bottlenecks can be identified and strengthened by investment in new facilities or capacity expansion. Second, such models can be applied by analyzing the planning of future investments in new facilities/capacities. The basis of this analysis is balancing demand and capacities at the aggregate level. In this case, integration of distribution network design and planning typically involves stochastic or simulation models (Santoso et al. 2005; Mula et al. 2010).

To answer the *first* question, in Fig. 6.6, a re-designed PDN structure is presented subject to smaller (as compared with Fig. 6.1) warehouse capacities at nodes 3, 7, 2 and 5, as well as smaller intensity of transportation channels 2→4 and 4→5.

The lower capacities result in a 16\$ decrease in fixed costs. Both for the optimistic and pessimistic scenarios, the same volume of delivered goods as in the initial distribution network structure can be realized. Total costs in the optimistic scenario are reduced from 251\$ to 235\$, and the profit increases from 49\$ to 65 \$. In the pessimistic scenario, total cost is 237.6\$ instead of 253.6\$, and the losses are reduced from 3.6\$ to a profit of 13.6\$.

Let us re-design the structure from Fig. 6.6 once again as shown in Fig. 6.7. The lower capacities result in a 33\$ decrease in fixed costs. For the optimistic scenario, the same volume of delivered goods as in the initial PDN structure can be realized. Total costs in the optimistic scenario are reduced from 251\$ to 217\$, and the profit increases from 49\$ to 82\$. In the pessimistic scenario, the volume of

Fig. 6.6 Re-designed distribution network structure

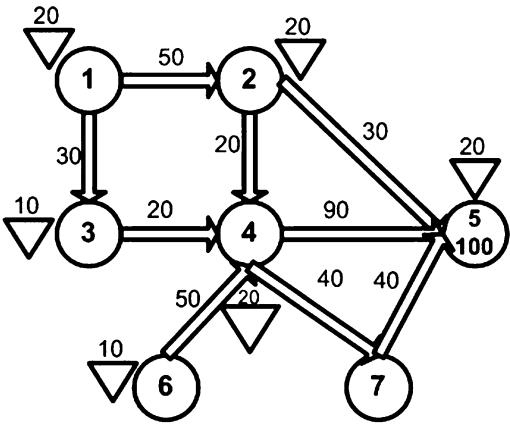


Fig. 6.7 Re-designed distribution network structure

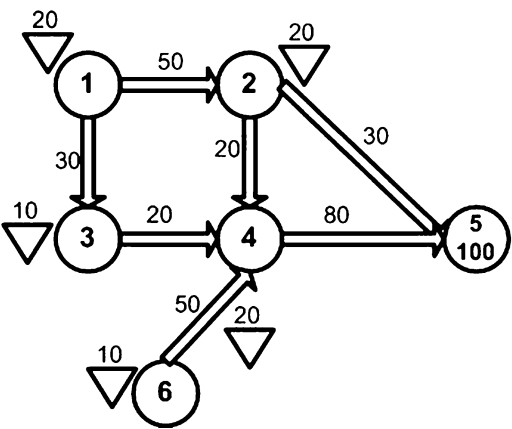
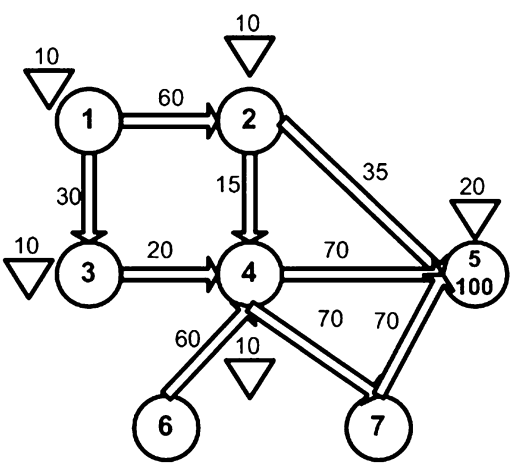


Fig. 6.8 “Ideal” distribution network structure



delivered goods decreases from 250 to 160 units. Total costs are 247.2\$ instead of 253.6\$, and the losses are increased from 3.6\$ to 87.2\$.

The *next* question is how to synthesize such an “ideal” distribution network structure that ensures a 100% service level in all possible scenarios. Analysis of the dual variables in the models for optimistic and pessimistic scenarios and the solving of the inverse problem facilitates synthesis of the “ideal” distribution network for a considered demand of 300 units (see Fig. 6.8).

In Fig. 6.9, the corresponding optimal distribution plans for optimistic and pessimistic scenarios are presented analogously to Fig. 6.2.

The planning results are summarized in Table 6.2.

It can be observed that in the re-designed distribution network, profit is achieved both in the optimistic and pessimistic scenarios because of the 100% service level (300 units of the delivered goods), decreased fixed costs (63\$ instead of 90\$) and

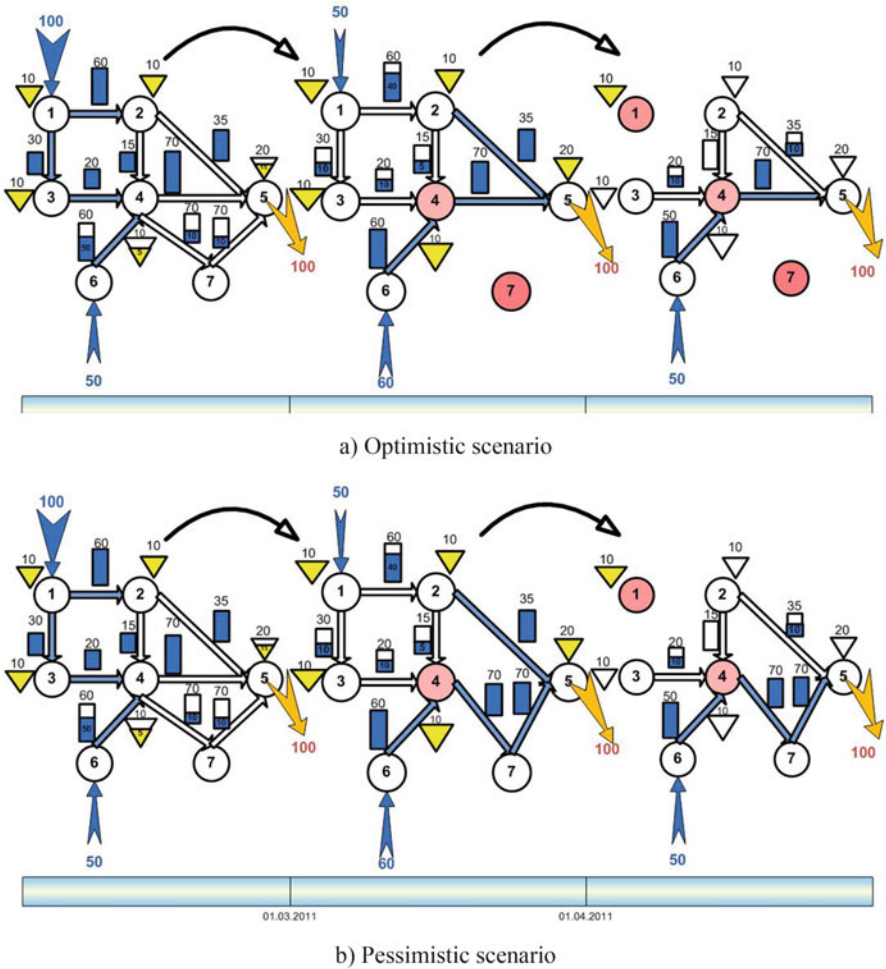


Fig. 6.9 Optimal distribution plans for the re-designed distribution network. (a) Optimistic scenario. (b) Pessimistic scenario (Ivanov et al. 2013)

inventory costs (8.4\$ instead of 8.4\$ and 12.6\$, correspondingly). In the optimistic scenario, the transportation cost has also been decreased from 28.6\$ to 27.8\$. In the pessimistic scenario, transportation cost has increased from 27.0\$ to 33.6\$, mainly because of the increase in the volume of the delivered goods. Through capacity alignment, fixed cost reduction, high service level and a tendency toward lower inventory and transportation costs, profit can be earned in the re-designed distribution network.

The *last* question addresses analysis of sourcing (order) quantities. In Table 6.3, a fragment of the experimental variation of order quantities is presented.

Table 6.2 Planning results for the re-designed PDN

Plan	Delivered goods	Costs						Profit
		Inventory	Return	Transport	Sourcing	Fixed	Total	
Optimistic	300 units	8.4\$ (120 units)	0	27.8\$	124\$ (310 units)	63\$	223.2	76.8
Pessimistic	300 units	8.4\$ (120 units)	0	33.6\$	124\$ (310 units)	63\$	229.8	70.2

Table 6.3 Experimental variation of order quantities

Order quantity	Interval 1		Interval 2		Interval 3
	Node 1	Node 6	Node 1	Node 6	Node 6
310	100	50	50	60	50
300	98	48	48	58	48
290	96	46	46	56	46
280	94	44	44	54	44
270	92	42	42	52	42
260	90	40	40	50	40
250	88	38	38	48	38
240	86	36	36	46	36
230	84	34	34	44	34

Figure 6.10 depicts the effects from aligning sourcing and distribution planning decisions.

From Fig. 6.10 it can be observed that maximal profit in the pessimistic scenario can be achieved by reducing order quantities at $k = 1$ (the reduction at node 1 of 13–18%, i.e., 82–87 units; the reduction at node 6 of 26–36%, i.e., 32–37 units). At $k = 2$ it is recommended to reduce order quantities at node 1 of 26–36% and at node 6 of 24–30%. At $k = 3$ it is recommended to reduce order quantities at node 6 of 26–36%.

6.5 Experiments for Manufacturing Supply Chain Structural Dynamics with Ripple Effect Considerations

6.5.1 Supply Chain Design Structural Dynamics

Consider a part of a supply chain in the automotive industry that is composed of two Tier 2 suppliers (nodes #1 and #2), one Tier 1 supplier (node #3), two assembly plants (nodes #5 and #6) and two markets (nodes #8 and #9) (see Fig. 6.11).

The following nodes represent the supply chain design elements:

- Tier 2 supplier#1: node #1
- Tier 2 supplier#2: node #2
- Tier 1 supplier: node #3
- Assembly plant #1: node #5
- Assembly plant #2: node #6
- Market #1: node#8
- Market #2: node#9

For computational experiments, the following data set has been used (Table 6.4).

For analysis, the management considers two structural dynamics scenarios (Table 6.5).

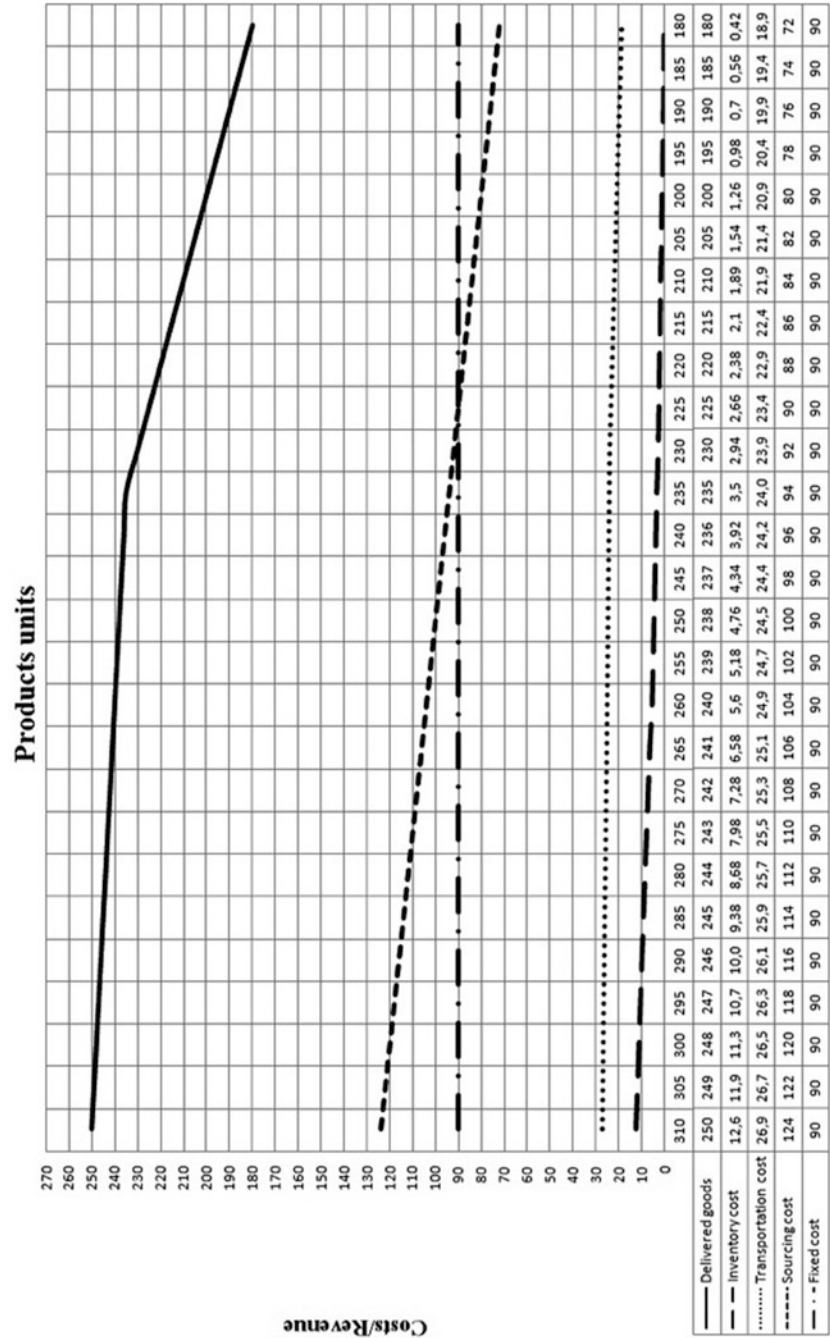


Fig. 6.10 Effects from aligning sourcing and distribution planning decisions (pessimistic scenario)

Fig. 6.11 Current structure of the supply chain

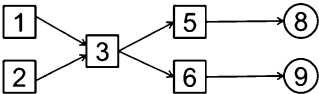


Table 6.4 Input data

Parameter	Value
Number of periods	6
Demand distribution over six periods	Market 1: 250-240-230-240-250-240 Market 2: 220-210-200-210-220-210
Delivery quantity to tier 1 supplier	From supplier #1: 400 units in each period From supplier #2: 100 units in each period
Maximum processing throughput capacities at plants	Tier 1 supplier: 550 units a period Assembly plants: 300 units a period each
Maximum transportation throughput capacity	Channel tier 2 supplier#1 to the tier 1 supplier: 500 units a period Channel tier 2 supplier#2 to the tier 1 supplier: 150 units a period Channel tier 1 supplier to the assembly plant #1: 300 units a period Channel tier 1 supplier to the assembly plant #2: 250 units a period Channel assembly plant #1 to the market #1: 280 units a period Channel assembly plant #2 to the market #2: 240 units a period
Maximum warehouse storage capacities	Tier 2 supplier#1: 150 units per period Tier 2 supplier#2: 70 units per period Tier 1 supplier: 250 units per period Assembly plant #1: 100 units a period Assembly plant #2: 100 units a period Market #1: 50 units a period Market #2: 50 units a period
Price of the final product. \$	65
Bill-of-material factor	1:1, i.e., one speedometer is needed for one cockpit, and one cockpit is needed for one car

Table 6.5 Optimistic and pessimistic scenarios of structural dynamics

Period	1	2	3	4	5	6
Disrupted elements in the optimistic scenario	—	6	6,1	5→8	—	2→3
Disrupted elements in the pessimistic scenario	1	1	4	4, 2	5→8	—

In the first scenario that we call “optimistic,” a disruption at the assembly plant #2 happens in the second period and destroys the capacity of this plant completely (100%). This disruption lasts two periods. In period #4, the capacity of this production plant is recovered completely (100%). In addition, in period number

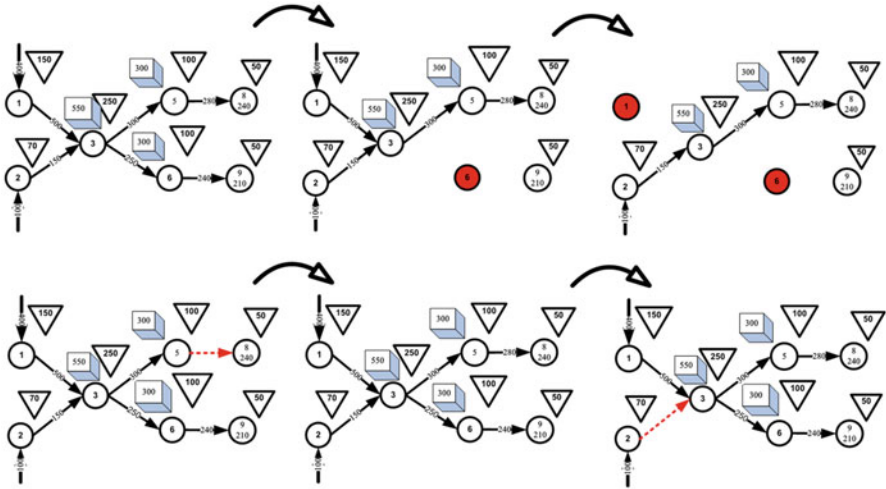


Fig. 6.12 “Optimistic” disruption scenario

#3 a fire at the Tier 2 supplier #1 happens and makes the deliveries from this supplier to the Tier 1 supplier in period #3 impossible. In the next period, the deliveries can run in normal mode again. Finally, due to strikes at a railway company in periods #4 and #6, the transportation channels between the assembly plant #1 and market#1 and between the Tier 2 supplier #2 and the Tier 1 supplier become unavailable, respectively (see Fig. 6.12).

Maximum processing throughput capacities are marked in rectangles, maximum transportation throughput capacities are presented on the arcs and maximum storage capacities are depicted in triangles. The disruptions are marked red. In Fig. 6.13, the so called “pessimistic scenario” is shown.

The following six alternative proactive strategies for supply chain design can be considered:

1. Increase in the flexibility of supplier #2 so that it delivers, under normal conditions, 100 units in each period and can extend the quantity to 400 units if need be
2. New back-up supplier is introduced at Tier 1 stage
3. A back-up assembly plant is introduced
4. Multiple sourcing strategy with alternative transportation channels
5. Increase in warehouse storage and processing capacity
6. Increase in transportation channel throughput capacity

The summary of these measure is shown in Fig. 6.14.

In regard to the processing and transportation throughput capacity of the new supply chain design elements, we assume the following: throughput capacity of new transportation channels is 120% of the processing throughput capacity of the

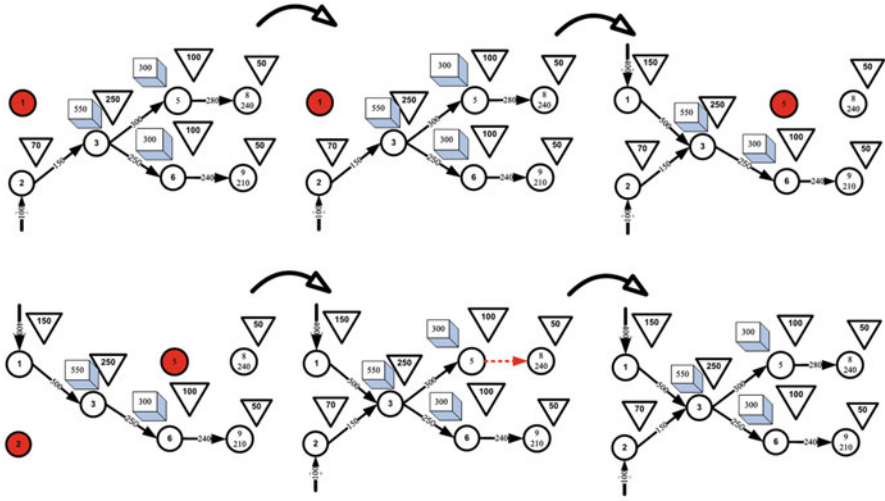
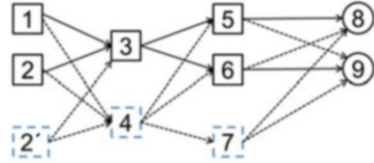


Fig. 6.13 “Pessimistic” disruption scenario (Ivanov et al. 2017)

Fig. 6.14 Possible extensions to supply chain structure (Ivanov et al. 2016)



outgoing node; processing capacity at node #4 is 250 units in each period, and processing capacity at node #7 is 150 units in each period.

For the computation of the ripple effect’s impact on the customer performance, we suggest introducing an index of performance impact (PI) that represents a relation between the planned KPI (key performance indicator) in a disruption-free mode and the real KPI in the event of disruption (Eq. 6.60):

$$PI = \frac{KPI_{plan}}{KPI_{disruption}} \quad (6.60)$$

We suggest using revenue and lost sales as a KPI for measuring the ripple effect’s impact on the performance of customer service levels. Such an index can be computed for each i -node in the supply chain, $i = 1, \dots, N$. Subsequently, we can compute a product of the i -PIs in order to calculate the overall PI in the supply chain (Eq. 6.61):

$$PI_{general} = \prod_{i=1}^N PI \quad (6.61)$$

6.5.2 Planning Results for Initial Supply Chain Design

In Fig. 6.15, the results of optimal planning subject to the given data set and the highest priority of the service level component in the objective function (Eq. 6.1) for the optimistic and pessimistic scenarios are presented.

Running the developed planning model on the assumption of the highest priority of the service level component in the goal function, the optimal solution for the

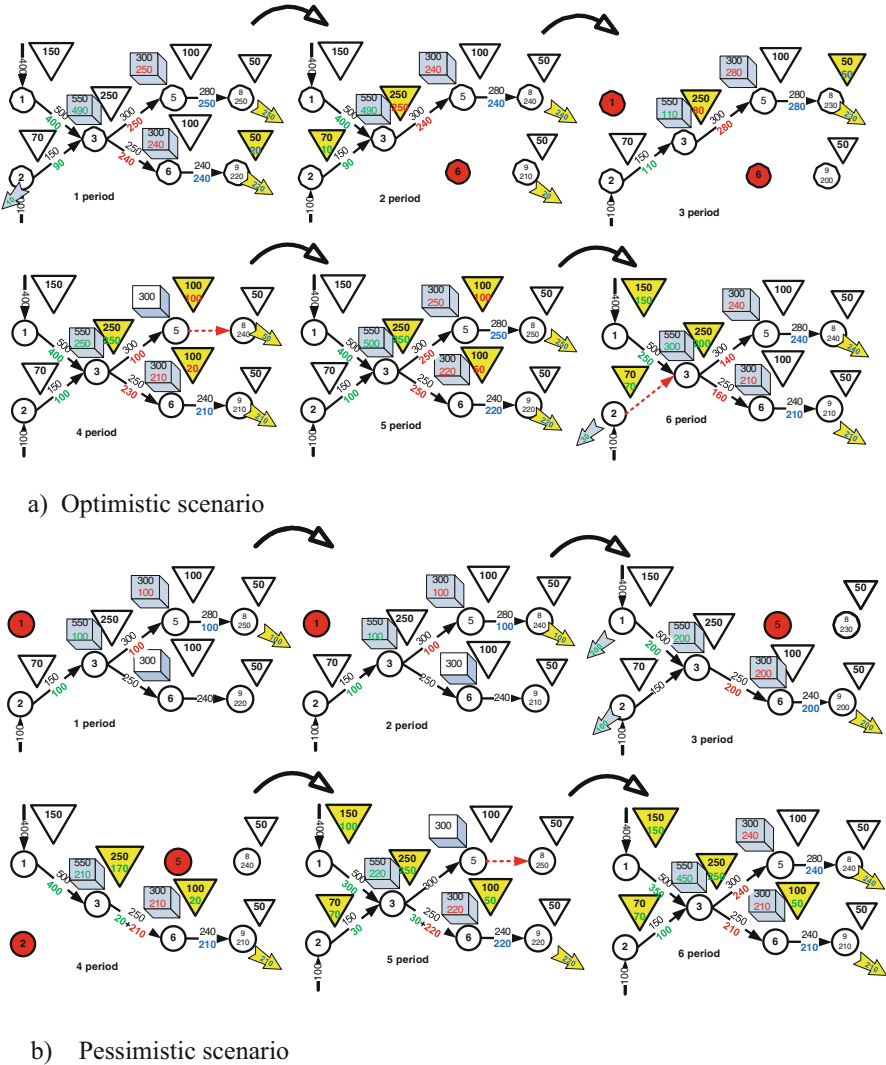


Fig. 6.15 Planning results for initial supply chain design (a) Optimistic scenario (b) Pessimistic scenario

optimistic scenario leads to a delivery of 2140 units, which is equivalent to a service level of 78.7%, subject to the estimated demand of 2720 units in six periods. For the pessimistic scenario, optimal solution delivers 1280 units, i.e. the service level is 47.1%.

In the optimistic scenario, the supply chain still remains profitable, but in the pessimistic scenario losses of \$13,390 arise. In comparison to the ideal case (no disruptions), in both optimistic and pessimistic scenarios the service level decreases to 78.7% and 47.1%, respectively. Moreover, profits would decrease to \$20,500 and \$-13,390 as compared to \$42,720, in the ideal case.

6.5.3 Planning Results for the Re-designed Supply Chain

In both cases considered in Sect. 6.5.2, the profits and service level (i.e., sales volume) significantly decrease. This is the starting point for supply chain managers to develop ways of increasing supply chain resilience. The central trade-off in this analysis is *efficiency vs resilience*. In the next step, the developed model is applied to analysis of six actions (defined in Sect. 6.5.1) for a possible resilience increase (measured through service level and sales volumes) subject to this trade-off.

In Table 6.6, the impact of different proactive policies to increase supply chain design resilience is summarized for the optimistic scenario.

As an example, the supply chain reconfiguration plan for action #4 is presented in Fig. 6.16.

Table 6.6 Performance impact of different resilience policies in the optimistic scenario

	Node #2 and channel 2→3	Node #4 and channels 4→5 and 4→6	Node #7 and channels 7→8 and 7→9	Channels 6→8 and 5→9	Actions 1 + 2	Actions 3 + 5
Performance indicator	Action 1	Action 2	Action 3	Action 4	Action 5	Action 6
Revenue	139,100	139,100	151,450	160,550	139,100	160,550
Transportation costs	28,280	26,600	24,320	29,640	28,880	33,400
Inventory holding costs	2680	3260	1300	920	3600	4080
Return costs	22,350	150	450	450	20,100	14,100
Fixed costs	13,100	15,200	12,350	12,600	16,300	18,400
Upstream costs	110,000	65,000	65,000	65,000	110,000	110,000
Recovery costs	2510	3310	2510	2990	3310	3310
Processing costs	8560	8560	9320	9880	8560	9880
Total costs	187,480	122,080	115,250	121,480	190,750	193,170
Profit	-48,380	17,020	36,200	39,070	-51,650	-32,620

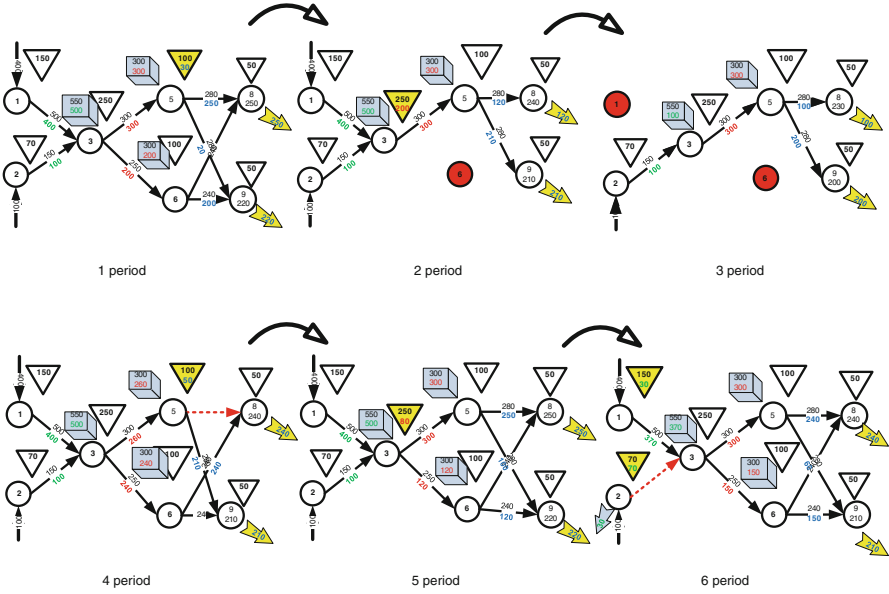


Fig. 6.16 Planning results for the re-designed supply chain (action #4)

It can be observed from Table 6.6 and Fig. 6.16 that structural changes significantly impact performance and resilience. The most significant contribution to increasing resilience is action #7 where a 100% service level can be achieved despite disruptions. Obviously, this is one of the most expensive actions as well. In this particular case, action #7 results in a negative profit. The highest profit can be achieved using actions #3 and #4, which can be considered for supply chain re-design. In the optimistic scenario, for action #3, the service level increases by 8.9%, and the profit rises by 76.2% as compared to the initial supply chain design. For action #4, the service level increases by 15.4% and the profit rises by 90.1%.

6.5.4 Quantifying the Ripple Effect

We use the computation results from Sects. 6.5.2 and 6.5.3 and compute the PI index using Eqs. (6.60) and (6.61). First, we compute PI for two markets individually using Eq. (6.60). In the next step, we aggregate these partial PI to general PI using Eq. (6.61). We consider supply chain sales (revenue) as the KPI for measuring the estimated annual magnitude of the ripple effect. To make the analysis more depictive, we restrict ourselves to PI consideration at the markets without PI analysis at the intermediate stage in the supply chain. This is an admissible restriction since the revenue KPI is directly related to the market stage in the supply chain. The results of the PI computation are shown in Table 6.7.

Table 6.7 PI computation results

	Initial	SCD 1	SCD 2	SCD 3	SCD 4	SCD 5	SCD 6
Maximum revenue market #8 in disruption-free scenario	94,250	94,250	94,250	94,250	94,250	94,250	94,250
Revenue market #8 in the opt. disruption scenario	81,900	82,225	82,470	81,900	81,900	82,225	82,470
PI market #8 in the opt. disruption scenario	1,150,794	1,146,245	1,150,794	1,150,794	1,150,794	1,146,245	1,14,284
Revenue market #8 in the pess. disruption scenario	28,600	15,600	15,600	15,600	15,600	15,600	15,600
PI market #8 in the pess. disruption scenario	3,295,455	6,041667	6,041667	6,041667	6,041667	6,041667	6,041667
Maximum revenue market #9 in disruption-free scenario	82,550	82,550	82,550	82,550	82,550	82,550	82,550
Revenue market #9 in the opt. disruption scenario	57,200	57,850	57,850	57,200	57,200	58,760	59,930
PI market #9 in the opt. disruption scenario	1,443,182	1,426,966	1,426,966	1,443,182	1,443,182	1,404,867	1,37,744
Revenue market #9 in the pess. disruption scenario	54,600	67,600	67,600	70,200	72,800	70,200	72,800
PI market #9 in the pess. disruption scenario	1,511,905	1,221,154	1,175,926	1,175,926	1,133,929	1,175,926	1,133,929

Let us present these results graphically and analyze their managerial meaning (Figs. 6.17, 6.18, and 6.19).

Table 6.7 and Figs. 6.17, 6.18, and 6.19 can be used as a dashboard for supply chain design comparison in regard to the ripple effect. The results can also help to analyze the disruption impact at different markets individually in order to derive recommendations for securing the supply and customer satisfaction. For the given data set, it can be observed that the supply chain for the market #2 (node #9) is

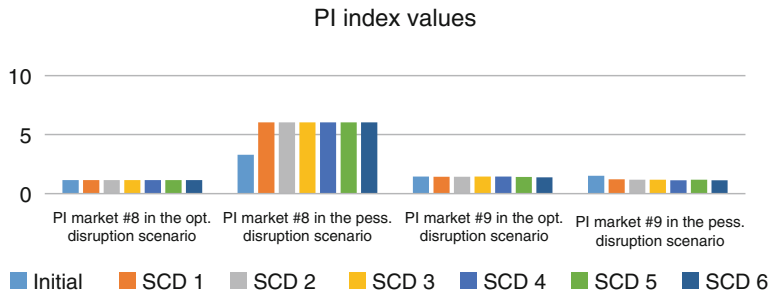


Fig. 6.17 PI computation for individual markets

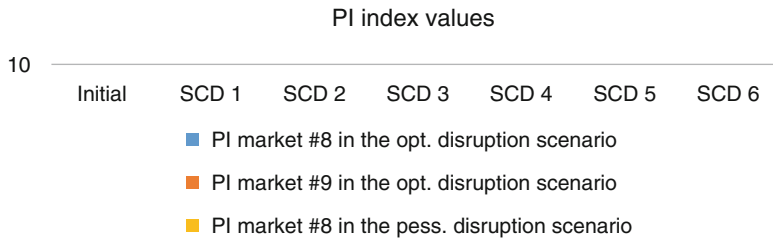


Fig. 6.18 PI computation for individual markets and different supply chain designs

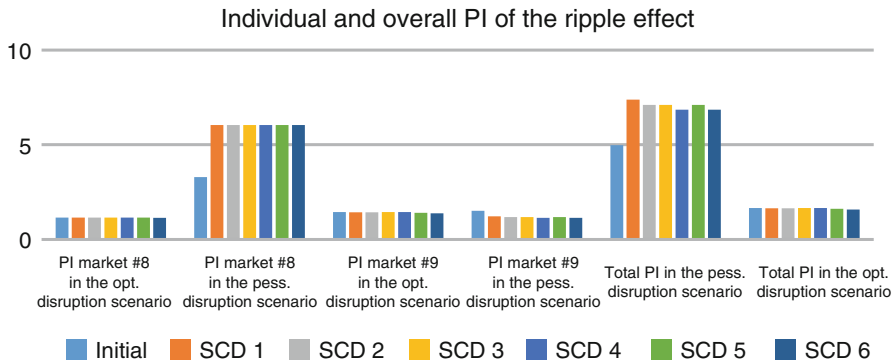


Fig. 6.19 Comparison of individual and total PI computation

much more resilient and less exposed to the ripple effect as compared to market #1 (node #8). In both scenarios, the PI for market #2 (node #9) does not exceed 1.51 whilst the maximum PI for market #1 (node #8) is 6.04.

In the case of the optimistic scenario, the lowest ripple effect can be observed in supply chain design #6 both at market #1 (node #8) and at market #2 (node #9), $PI = 1.14284$ and $PI = 1.3744$, respectively. In the case of the pessimistic scenario, the lowest ripple effect can be observed in the initial supply chain design at market #1 (node #8, $PI = 3.295455$), while at market #2 (node #9), minimum $PI = 1.133929$ for supply chain designs #4 and #6.

In total cumulative PI in the optimistic scenario, a large gap between the minimum PI (i.e., initial SCD) and PI for other supply chain designs can be observed in Fig. 6.19. At the same time, the total PI values in the pessimistic scenario are very close to each other with a small advantage for supply chain design #6.

For the example considered, it becomes obvious that market #1 (node #8) is highly exposed to ripple effect in the negative scenario, whilst market #2 (node #9) shows a disruption-resistance and performs in the pessimistic scenario even better than in the optimistic one.

In joint analysis of two markets, the initial supply chain design is recommended since it exhibits the lowest ripple effect. At market #8, risk-sharing contracts are recommended with the customers. In addition, storage capacity extensions and higher safety stocks can be applied in this market.

6.5.5 Impact of Recovery Speed

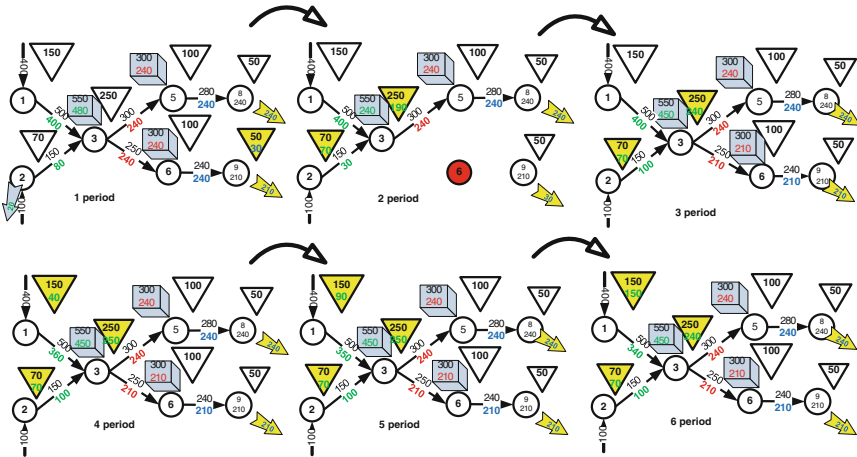
For further analysis, the management considers three recovery scenarios subject to disruption in node #6 in the second period (Table 6.8).

In Fig. 6.20, the results of optimal re-planning subject to the given data set and the highest priority of the service level component in the goal function (Eq. 6.1) for three scenarios are presented.

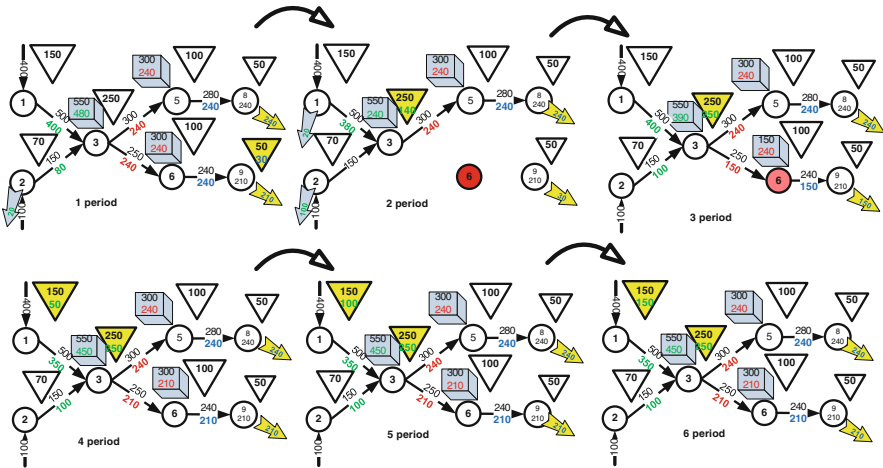
For the given data, the fast and expensive recovery policy is the most effective one. Using this policy, the highest profit and revenues can be achieved. The results can also assist in analysis of the achieved service level (subject to planned and real revenues) in different periods and for different recovery policies. For example, in the fast and expensive policies, the real service level corresponds to the planned service level except for period #2, where service level shrinks to 60%.

Table 6.8 Capacity availability for node #6 (in %)

Period	1	2	3	4	5	6
Quick and expensive recovery	100	0	100	100	100	100
Normal recovery	100	0	50	100	100	100
Slow and efficient recovery	100	0	30	50	100	100



Quick and expensive recovery



Normal recovery

Fig. 6.20 Re-planning results for different recovery speeds (Ivanov et al. 2017)

Table 6.9 compares the performance impact of different recovery policies and return flows subject to the simultaneously optimized re-configuration plans for material flows. It can be observed that the best downstream performance impact (i.e., profit at \$28,090 and service level at 93.3%) can be achieved with a fast and expensive recovery strategy. This recovery policy also provides the lowest return costs of \$300 in the upstream supply chain, as compared to \$2100 in the normal recovery policy and \$4500 in the slow and cheap recovery policy.

Table 6.10 Comparison of the gradual recovery and [0–1] recovery views

Performance indicators	Gradual recovery considerations			[0–1] recovery considerations		
	Fast and expensive	Normal	Slow and efficient	Fast and expensive	Normal	Slow and efficient
Revenue	163,800	159,900	152,750	163,800	150,150	136,500
Transportation costs	31,200	30,520	29,200	31,200	30,440	26,200
Inventory holding costs	3660	2940	2140	3660	3340	2800
Return costs	300	2100	4500	300	3300	6450
Fixed costs	13,100	13,100	13,100	13,100	13,100	13,100
Upstream costs	75,000	75,000	75,000	75,000	75,000	75,000
Recovery costs	2370	2370	2370	2370	2370	2370
Processing costs	10,080	10,020	9400	10,080	9240	8400
Total costs	135,710	136,050	135,710	135,710	136,790	134,320
Profit	28,090	23,850	17,040	28,090	13,360	2180
Average service level	93.3	91.1	87.1	93.3	85.6	77.8

explained since the fast and expensive recovery policy in our experiment setting allows full recovery within one period. A difference could be achieved if smaller time sub-periods were considered within the recovery period. It can be observed from Table 6.10 that gradual capacity recovery consideration allows computation of more realistic performance impact measures and material flow re-direction plans.

6.6 Managerial Insights

Disruption risks may result in the ripple effect and structure dynamics in the supply chain. It is notable that the scope of the rippling and its performance impact depend both on robustness reserves (e.g., redundancies like inventory or capacity buffers) and speed and scale of recovery actions. In many practical settings, companies need analysis tools to estimate both supply chain efficiency and supply chain resilience. For supply chain resilience, the impacts of recovery actions subject to different disruptions and performance indicators need to be estimated.

The results of this study contribute to the support of decisions in these practical problems. The developed model can help supply chain risk managers to identify how resilient the existing supply chain design is for different disruption scenarios. The model also considers recovery strategies (i.e., reconfiguration) that can be used by supply chain managers and translated into the supply chain design and supply chain plan changes.

With the use of the developed approach, supply chain managers can compare different possible supply chain designs according to their resilience (measured through the sales volumes or service level) using the proposed model. Since the computation includes recovery actions, the developed model can help to identify opportunities for reducing disruption and recovery costs by supply chain re-design and re-planning.

The proposed model analyzes effective ways to recover and re-allocate resources and flows after a disruption. It also considers disruption durations and operative reactions to disruptions. Such a model can be used by supply chain risk specialists to analyze the performance impact of different resilience and recovery actions and adjust mitigation and recovery policies with regard to critical supply chain design structural elements and supply chain planning parameters.

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Chapter 7

Control-Theoretic Models and Algorithms for Supply Chain Scheduling with Capacity Disruption and Recovery Considerations

7.1 Problem Statement

7.1.1 Coordinated Supply Chain Scheduling Problem

Coordinated decision-making distinguishes the *supply chain scheduling* problem as a specific research topic (Ivanov et al. 2017). In supply chains, after processing at the production plants (i.e., the suppliers), finished products can be delivered to the next production stage in the supply chain or to the customers. In terms of scheduling theory, we have a *flow shop* process (Johnson 1954; Gonzalez and Sahni 1978; Gupta et al. 2001). At the same time, at each stage in this *multistage* environment, alternative executors (e.g., production plants and transportation modes) exist which are unequal their processing intensities. Once a job is assigned to a supplier, the processing of the operations of this job can be done either in job shop or flow shop modes. Thus, the supply chain is a *hybrid flow shop* (Ribas et al. 2010). This requires both machine assignment and sequencing tasks.

The studies on supply chain scheduling by Hall and Potts (2003), Agnetis et al. (2006), Ivanov and Sokolov (2012) and Choi et al. (2013) developed major frameworks, classifications and solution techniques in this research domain. Details of mathematical models across the publications on supply chain scheduling differ, but most share a basic set of attributes: a finite sets of jobs, customers, and suppliers, a fixed time span over which a schedule should be generated and multi-stage schedule coordination.

In recent years, disruptions in supply chain capacities have occurred in greater frequency and intensity. These events rippled quickly through global supply chains and caused significant losses in revenue (Ivanov et al. 2014). In this context, the issues of supply chain robustness have become more and more important. When handling these issues, new challenges for supply chain scheduling exist that concern uncertainty and disruptions as well as coordination activities (Sawik 2013). Most

recently, Sawik (2015) pointed out that although the impacts of schedule coordination on supply chain performance may be substantial, the research on coordinated scheduling optimization is fairly recent and there is still a research gap in terms of the magnitude of these impacts.

7.1.2 *Supply Chains Scheduling with Capacity Disruptions and Recovery*

In this study, we focus on coordinated supply chain scheduling with continuous material flows. Supply chains in continuous production systems comprise multi-stage networks of suppliers. Continuous flow scheduling problems have their place in many industries such as gas, oil, chemicals, glass and fluids production as well as production of granular goods and steel details (Shah 2004; Puigjaner and Lainez 2008; Subramanian et al. 2013; Ivanov and Sokolov 2013a, b; Ivanov et al. 2016a, b; Božek and Wysocki 2015). Since the supply chain process typically has a multi-stage structure, the issues of capacity and supply disruptions are crucial for overall supply chain schedule performance. The disruptions in processing and transportation capacities may result in increased flow times, makespan, tardiness, and decreased throughput, on-time delivery, and supply chain service level. Given this, dynamic schedule representation and schedule robustness analysis become important issues. Moreover, coordination needs to be included in the scheduling and robustness analysis.

The main points of this study can be stated as follows:

- We consider a hybrid discrete/continuous flow shop supply chain with job shop processes at each supplier stage and study it with the help of dynamic optimal control models.
- We develop operations, channel, resource and flow control models with multiple objectives.

Consider the following problem structure (see Fig. 7.1). This problem structure relates to a commonly adopted supply chain scheduling model (Sawik 2014; Ivanov et al. 2016a).

Let us introduce the following definitions.

“*Job*” comprises a set of operations to be completed at a supplier level according to some criteria such as makespan or due dates.

“*Operation*” is an action needed to complete a production process. Each operation is characterized by some parameters such as flow time or processed quantity.

“*Supplier*” is a processing plant in the supply chain.

“*Channel*” is a unit needed for processing or delivering the products; in manufacturing, a channel can be a machine, a cell or a processing center; in logistics, a channel can be, e.g., a road.

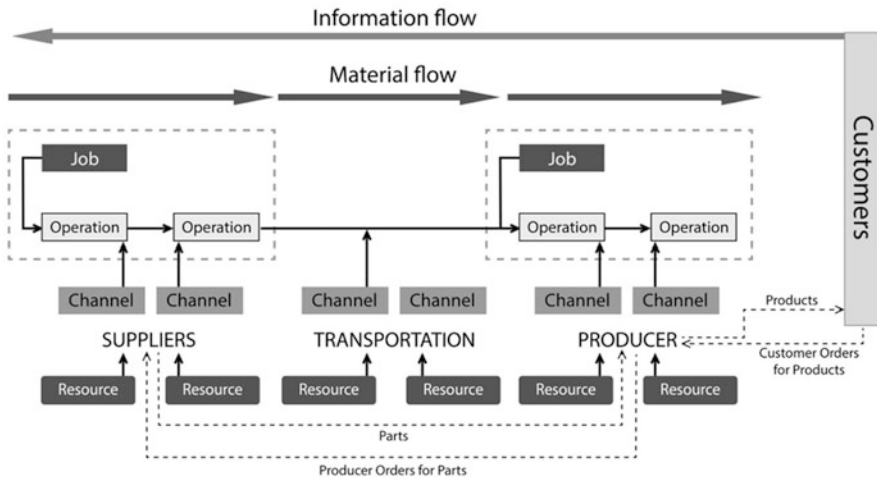


Fig. 7.1 Problem structure

“*Resource*” is a unit needed for processing an operation in a channel; it can be a material, a technical device or a truck.

“*Flow*” is a material flow characterizing by real and planned quantities, processing/transportation rates and a speed of flow volume change.

Operations are executed according to a varying sequence of processing stages, each of which contains some alternative suppliers. Once a job is assigned to a supplier, the operations of this job are executed either in flow or job shop mode through some alternative channels. For transportation, different alternative channels are available.

In addition, the problem considered captures the following features:

- Processing speed of each machine is described as a time function and is modelled by material flow functions (integrals of processing speed functions) and resulting processing time is, in general, channel dependent;
- Processing, transportation and warehouse capacities are included;
- Setups are included in the analysis;
- Lot-sizes and release dates are known;
- Temporary capacity unavailability is included both in planned and perturbed modes;
- Capacity degradation/recovery is considered;
- Impact of disturbances and coordination on performance with recovery consideration is included in the analysis with the help of the theory of attainable sets;
- Material supply dynamics is described in the resource control model.

The following performance indicators (objective functions) are considered:

- Throughput
- Lead-time

- Makespan
- Waiting time
- Total lateness
- Time-to-recovery
- Equal utilization of channels in the supply chain.

The *first task* is to find a coordinated schedule in the supply chain, i.e., to assign the jobs at each stage to alternative suppliers and determine start and completion times for each operation at the machines at each supplier. The *second task* is to analyze the impact of disruptions in capacities and supply on the planned schedule performance and to develop schedules for recovery actions.

7.2 Modelling Approach

7.2.1 Literature on Coordinated Supply Chain Scheduling

In considering mathematical models on supply chain scheduling, Chen (2010) recommends considering such a problem as an integrated production and outbound distribution scheduling problem. A peculiarity of such a simultaneous consideration is that both machine structures and flow parameters may be uncertain and change in dynamics and are, therefore, non-stationary. In the context of supply chains and taking into account standard scheduling methods, uncertainty in supply chain schedule parameters is accepted by the research community as an important and timely topic (Hall and Potts 2003; Agnetis et al. 2006).

The study by Hall and Potts (2003) considered the benefits and challenges of *coordinated* decision-making within supply chain scheduling. Chen and Hall (2007) studied conflicts and coordination in assembly systems where there are several suppliers providing components. Sarker and Diponegoro (2009) considered optimal production plans and shipment schedules in a supply chain with multiple suppliers, one manufacturer and multiple buyers subject to the known demands of buyers. The overview by Chen (2010) identified that, in integrated scheduling and logistics problems, it is necessary to define completion, departure and delivery times for each job subject to time-based, cost-based or revenue-based indicators. Hall and Liu (2011) investigated capacity allocation by a manufacturer subject to orders from distribution centers. Ullrich (2013) integrated production and outbound distribution scheduling in order to minimize total tardiness. Choi et al. (2013) studied a supply chain scheduling and co-ordination problem where the manufacturer was a decision maker that selected the orders and aimed to maximise its own profit.

The studies on schedule robustness focus on closing the gap between theory and practice regarding the uncertain nature of real environments for schedule execution. A schedule that is able to achieve planned performance in spite of disruptions is called *robust* (Sotskov et al. 2013). Robustness analysis or robust optimization

approaches for related problems in assembly line design and scheduling have been considered, for example, in the studies by (Sotskov et al. 2006; Dolgui and Kovalev 2012a; b; Hazir and Dolgui 2013; Gurevsky et al. 2012, 2013; Hazir and Dolgui 2015). The method developed here is complementary to robust discrete optimization.

With the help of control theory, coordination issues have been mostly studied in light of supply chain contracting (Gan et al. 2005; Yang et al. 2011) or manufacturing system dynamics (Sagawa and Nagano 2015). Kogan and Khmelnitsky E. (1995) developed an optimal control method for aggregate production planning in large-scale manufacturing systems with capacity expansion and deterioration and proved necessary optimality conditions for a generalized problem of production scheduling. Wang et al. (2013) proposed a distributed scheduling algorithm called a closed-loop feedback simulation approach that includes adaptive control of the auction-based bidding sequence to prevent the “first bid, first serve” rule and may dynamically allocate production resources to operations. Ivanov et al. (2016b) applied optimal program control to distributed supply chain scheduling in the context of smart factories and Industry 4.0.

It can be observed in literature that the dynamics of schedule execution and coordination in the supply chain have been frequently neglected. Robustness in a continuous time domain has not yet been explored in scheduling settings, although it has been extensively investigated in system dynamics and control theory (Mayne et al. 2000; Ivanov et al. 2012; Ivanov and Sokolov 2013). Recent applications of control theory and optimal program control to supply chain coordination and scheduling have been multi-faceted, but do not consider both optimal control for supply chain scheduling and robust schedule coordination even if they include non-stationary processes and accuracy of continuous time (Chen et al. 2012).

7.2.2 Hybrid Optimal Control-Mathematical Programming Approach to Coordinated Supply Chain Scheduling

The underlying theory for studying multi-stage, multi-period dynamic systems with continuous variables and performance indicators accumulated over time is optimal control theory in general, and optimal program control in particular (Athaus and Falb 1966; Lee and Markus 1967; Sethi and Thompson 2000). At the same time, a direct application of optimal program control to a pure combinatorial problem is questionable.

The basic *technical idea* of our approach is that the elements of optimal program control can extend the existing mathematical programming scheduling techniques. For this reason, we do not use optimal program control for solving the combinatorial problem, but rather to enhance the existing mathematical programming algorithms in terms of non-stationarity, flow control and continuous material flows. If the control variables are presented as binary variables, it might become possible to

incorporate them into the assignment problem. We apply methods of discrete optimization to combinatorial tasks within certain time intervals and use the optimal program control with all its advantages (i.e., accuracy of continuous time, integration of planning and control, and the operation execution parameters as time functions) for (1) flow control within operations and (2) interlinking the decomposed solutions.

The basic *computational idea* of this approach is that operation execution and machine availability are dynamically distributed in time over the planning horizon. As such, not all operations and machines are involved in decision making at the same time. Therefore, it becomes quite natural to transition from large-size allocation matrices with a high number of binary variables to a scheduling problem that is dynamically decomposed. Following an approach to decompose the solution space and to use exact methods over its restricted sub-spaces, we propose using optimal program control theory for the dynamic decomposition of the scheduling problem.

Optimal program control is primarily used for dynamic decomposition, but not for calculations. The computational procedure is transferred to mathematical programming methods (Ivanov et al. 2013, 2014). The solution at each time point is calculated with mathematical programming. Optimal program control is used for modeling the execution of the operations and interlinking the mathematical programming solutions over the planning horizon. Hence, the solution procedure becomes independent of the continuous optimization algorithms and can be of discrete nature, e.g., an integer assignment model. The maximum principle guarantees that the optimal solutions of the instantaneous problems give an optimal solution to the overall problem (Pontryagin et al. 1964; Boltyanskiy 1973; Sethi and Thompson 2000).

7.3 Formal Model

According to the problem statement (see Fig. 7.1), we need to describe and synchronize the following processes (Ivanov et al. 2016a):

- Customer order fulfillment dynamics in regard to operations scheduling and sequencing;
- Production machine and transportation dynamics in regard to the assignment of operations to channels;
- Material supply dynamics in regard to supplier selection at each supply chain stage;
- Processing and shipment dynamics in regard to processing and transportation channels.

For this purpose, the scheduling model comprises models of operations control (for customer order fulfillment dynamics), channel control (production machine and transportation dynamics), resource control (material supply dynamics) and flow control (processing and shipment dynamics). In Sect. 7.3, we describe these models

in deterministic form. In Sect. 7.4, a general schema with uncertainty consideration (i.e., with perturbation impacts) will be presented.

7.3.1 Notations

Consider the following sets (note that indices (o), (k), (r) and (f) describe the relations of the sets to operations (o), channels (k), machines (r), and material flows (f), respectively):

- set of jobs $A = \{A_\nu, \nu \in N\}$ that are composed of a set of operations, where N is a set of job numbers;
- set of suppliers $B = \{B_i, i \in W\}$ and set of channels at each supplier $C = \left\{ C_\lambda^{(i)}, \lambda \in \Lambda_i^k, i \in W \right\}$, where W is a set of supplier numbers and Λ is a set of channel numbers;
- set of manufacturing operations that can be fulfilled at the supplier $B^{(i)}$ $D^{(i)} = \left\{ D_{\mathfrak{x}'}^{(i)}, \mathfrak{x}' \in K_i^{(o)} \right\}$, where K_i is a set of operation numbers;
- set of logistics operations $D^{(i,j)} = \left\{ D_{\mathfrak{x}}^{(i,j)}, \mathfrak{x} \in K_{<i,j>}^{(o)} \right\}$ subject to transportation between $B^{(i)}$ and $B^{(j)}$, where $K_{i,j}$ is a set of operation numbers;
- set of resources in the supply chain $\Phi = \left\{ \left\{ \Phi S_\pi^{(i)} \right\} \cup \left\{ \Phi N_\mu^{(i)} \right\}, i \in W, \pi \in K_i^{(r,1)}, \mu \in K_i^{(r,2)} \right\}$, where W is a set of operation numbers; $\Phi S^{(i)} = \left\{ \Phi S_\pi^{(i)}, \pi \in K_i^{(r,1)} \right\}$ is a set of storable resources at $B^{(i)}$ and $\Phi N^{(i)} = \left\{ \Phi N_\mu^{(i)}, \mu \in K_i^{(r,2)} \right\}$ is a set of non-storable resources at $B^{(i)}$; K are the sets of resource numbers;
- set of material flows $P = \left\{ \left\{ P_{<\mathfrak{x}',\rho>}^{(i)} \right\} \cup \left\{ P_{<\mathfrak{x},\rho>}^{(i,j)} \right\}, \rho \in K_i^{(f)} \right\}$;
- set of material flows for ρ -types of materials $P^{(i)} = \left\{ \left\{ P_{<\mathfrak{x}',\rho>}^{(i)} \right\}, \rho \in K_i^{(f)} \right\}$ subject to $B^{(i)}$;
- set of material flows for ρ -types of materials $P^{(i,j)} = \left\{ P_{<\mathfrak{x},\rho>}^{(i,j)}, i, j \in W, \rho \in K_i^{(f)} \right\}$ subject to $B^{(i)}$ and $B^{(j)}$;
- sets $\Gamma_{\nu 1}, \Gamma_{\nu 2}$ of “and” and “or” precedence relations for different jobs and set $\Gamma_{i\mathfrak{x} 1}, \Gamma_{i\mathfrak{x} 2}$ of “and” and “or” precedence relations for operations $D_{\mathfrak{x}}^{(i,j)}$ and $D_{\mathfrak{x}'}^{(i)}$ respectively.

Let t be current instant of time, $T = (t_0, t_f]$ the scheduling horizon, and t_0 (t_f) the start (end) instant of time for the scheduling horizon, respectively.

Assume that manufacturing and transportation capacities may be disrupted and:

- a supplier’s availability can be described by a given preset matrix time function $\varepsilon_{ij}(t)$ of time-spatial constraints; we have $\varepsilon_{ij}(t) = 1$, if the delivery capacity between B_i and B_j is available and $\varepsilon_{ij}(t) = 0$, otherwise;

- a channel's availability can be described by the function $\Theta_{i\alpha j\lambda}(t)$ (or $\Theta_{v\alpha j\lambda}(t)$) that is equal to 1, if there are available channels $C_{\lambda}^{(i)}$ и $C_{\lambda}^{(j)}$ for B_i and B_j at time $t \in T$ for processing $D_{\alpha}^{(inj)}$ and equals 0, otherwise.

Manufacturing and logistics capacity degradation/recovery dynamics can be described by a continuous function of perturbation impacts $\xi_{ij}((t))$; $\xi_{ij}((t)) = 1$ if the channel between B_i and B_j is 100% available and $\xi_{ij}((t)) = 0$ if the channel is disrupted fully. All other values for $\xi_{ij}((t))$ in the interval $[0;1]$ are possible.

7.3.2 Dynamic Model for the Operation control Processes (Model M_o)

The formal statement of the scheduling problem is produced as a dynamic interpretation of the operations execution processes (Ivanov et al. 2016a, b). The list of indexes used in the models in Sect. 7.3 is as follows:

Notation	Meaning
v	Job index
n	Running numbers of a job
α	Operation index
s	Running numbers of an operation
i, j	Supplier index
m	Running numbers of a supplier
λ	Channel index
l	Running numbers of a channel
ρ	Product flow index
π	Storable resource index
μ	Nonstorable resource index
η	Replenishment cycle
$\tilde{\rho}, \tilde{\rho}$	Running numbers of replenishment cycles
α, β	Indices of the precedence relations “and,” “or” for jobs
$\tilde{\alpha}, \tilde{\beta}$	Indices of the precedence relations “and,” “or” for operations
(o), (k), (r), (f)	Indexes to describe the relations of the respective sets to operations (o), channels (k), suppliers (r), and material flows (f)
t	Current instant of time

7.3.2.1 Process Model of Operation Execution

$$x_{\nu}^{(0,1)} = \sum_{j=1}^m u_{\nu j}^{(0,1)}; \quad x_{i\alpha}^{(0,2,\nu)} = \sum_{j=1}^m \sum_{\lambda=1}^{l_j} \varepsilon_{ij}(t) \Theta_{i\alpha j \lambda}(t) u_{i\alpha j \lambda}^{(0,2,\nu)}; \quad x_{\nu j}^{(0,3)} = u_{\nu j}^{(0,3)} \quad (7.1)$$

7.3.2.2 Constraints

$$\sum_{j=1}^m u_{\nu j}^{(0,1)} \left[\sum_{\alpha \in \Gamma_{\nu 1}} \left(a_{\alpha}^{(0,1)} - x_{\alpha}^{(0,1)}(t) \right) + \prod_{\beta \in \Gamma_{\nu 2}} \left(a_{\beta}^{(0,1)} - x_{\beta}^{(0,1)}(t) \right) \right] = 0 \quad (7.2)$$

$$\sum_{\lambda=1}^{l_j} u_{i\alpha j \lambda}^{(0,2,\nu)} \left[\sum_{\tilde{\alpha} \in \Gamma_{i\alpha 1}} \left(a_{\tilde{\alpha}}^{(0,2,\nu)} - x_{\tilde{\alpha}}^{(0,2,\nu)}(t) \right) + \prod_{\tilde{\beta} \in \Gamma_{i\alpha 2}} \left(a_{\tilde{\beta}}^{(0,2,\nu)} - x_{\tilde{\beta}}^{(0,2,\nu)}(t) \right) \right] = 0 \quad (7.3)$$

$$\sum_{\nu=1}^u u_{\nu j}^{(0,1)}(t) \leq 1, \quad \forall j; \quad \sum_{j=1}^m u_{\nu j}^{(0,1)}(t) \leq 1, \quad \forall j; \quad u_{\nu j}^{(0,1)}(t) \in \{0, 1\} \quad (7.4)$$

$$u_{i\alpha j \lambda}^{(0,2,\nu)}(t) \in \{0, u_{\nu j}^{(0,1)}\}; \quad u_{\nu j}^{(0,3)}(t) \in \{0, 1\}; \quad u_{\nu j}^{(0,3)} \left(a_{j s_i}^{(0,2,\nu)} - x_{j s_j}^{(0,2,\nu)}(t) \right) = 0 \quad (7.5)$$

7.3.2.3 Start and End Conditions

$$h_0^{(o)} \left(x^{(o)}(T_0) \right) \leq O; \quad h_1^{(o)} \left(x^{(o)}(T_f) \right) \leq O. \quad (7.6)$$

7.3.2.4 Objective Functions

$$J_1^{(o)} = \sum_{\nu=1}^n \sum_{j=1}^m u_{\nu j}^{(o,3)}(T_f) \quad (7.7)$$

$$J_{<2,\alpha,\nu>}^{(o)} = \sum_{i=1}^m \sum_{j=1}^m \left(x_{\alpha i}^{(o,3)}(T_f) - x_{\nu j}^{(o,3)}(T_f) \right) \quad (7.8)$$

$$J_3^{(o)} = T_f - \sum_{j=1}^m x_{n j}^{(o,1)}(T_f) \quad (7.9)$$

$$J_{<4,i,\nu>}^{(o)} = \sum_{\nu,j,\lambda,\mathfrak{x}} \int_{T_0}^{T_f} \varepsilon_{ij}(\tau) \Theta_{i\mathfrak{x}j\lambda}(\tau) u_{i\mathfrak{x}j\lambda}^{(0,2,\nu)}(\tau) d\tau \quad (7.10)$$

$$J_{<5,i>}^{(o)} = \sum_{\nu,j,\mathfrak{x}} \int_{T_0}^{T_f} \left[\varepsilon_{ij}(\tau) - \varepsilon_{ij}(\tau) u_{i\mathfrak{x}j\lambda}^{(0,2,\nu)}(\tau) \right] d\tau \quad (7.11)$$

$$J_6^{(o)} = \sum_{i=1}^m \sum_{\mathfrak{x}=1}^{s_i} \left(a_{i\mathfrak{x}}^{(o,2,\nu)} - x_{i\mathfrak{x}}^{(o,2,\nu)}(T_f) \right)^2 \quad (7.12)$$

$$J_7^{(o)} = \sum_{\nu=1}^n \sum_{i=1}^m \sum_{\mathfrak{x}=1}^{s_i} \sum_{j=1}^m \sum_{\lambda=1}^{l_j} \int_{T_0}^{T_f} \tilde{\beta}_{i\mathfrak{x}}^{(\nu)}(\tau) u_{i\mathfrak{x}j\lambda}^{(0,2,\nu)}(\tau) d\tau \quad (7.13)$$

The multi-objective resolution for this model and further models will be discussed later in this Chapter. We also refer to the study (Ivanov and Sokolov 2012) for multi-objective resolution of optimal control scheduling models.

7.3.2.5 Parameters

$a_{\alpha}^{(o,1)}, a_{\beta}^{(o,1)}, a_{i\alpha}^{(o,2,\nu)}, a_{i\beta}^{(o,2,\nu)}, a_{is_i}^{(o,2,\nu)}, a_{i\mathfrak{x}}^{(o,1,\nu)}$ are the planned manufacturing/transportation quantities for each operation (i.e., the end conditions); these values have to be reached in $x_{\alpha}^{(o,1)}(t), x_{\beta}^{(o,1)}(t), x_{i\alpha}^{(o,2,\nu)}(t), x_{i\beta}^{(o,2,\nu)}(t), x_{is_i}^{(o,2,\nu)}(t), x_{i\mathfrak{x}}^{(o,1,\nu)}(t)$ at $t = T_f$;

$\mathbf{h}_0^{(o)}, \mathbf{h}_1^{(o)}$ are known differential functions for setting the start and end conditions subject to state variables $\mathbf{x}^{(o)} = \left\| x_1^{(o,1)}, \dots, x_n^{(o,1)}, x_{11}^{(o,2)}, \dots, x_{ms_m}^{(o,2)}, x_{11}^{(o,3)}, \dots, x_{nm}^{(o,3)} \right\|^T$ at $t = T_0$ and $t = T_f$.

7.3.2.6 Decision Variables

$x_{\nu}^{(0,1)}(t)$ is a state variable characterizing the flow time for job A_{ν} at each moment t ; $x_{i\mathfrak{x}}^{(0,2,\nu)}(t)$ is a state variable characterizing the flow time of the operations $D_{\mathfrak{x}}^{(i)}$ or $D_{\mathfrak{x}}^{(i,j)}$; $x_{\nu}^{(0,3)}(t)$ is a state variable characterizing the gap between the planned completion time for all jobs and the actual completion time of the job A_{ν}

$u_{\nu j}^{(0,1)}(t), u_{i\mathfrak{x}j}^{(0,2,\nu)}(t), u_{\nu j}^{(0,3)}(t)$ are control variables; if $u_{\nu j}^{(0,1)}(t) = 1$, if we have a transportation of a job A_{ν} to B_j ; $u_{\nu j}^{(0,1)}(t) = 0$ – otherwise; $u_{i\mathfrak{x}j\lambda}^{(0,2,\nu)}(t) = 1$, if operation $D_{\mathfrak{x}}^{(i)}$ or $D_{\mathfrak{x}}^{(i,j)}$ is assigned to a λ -channel, $u_{i\mathfrak{x}j\lambda}^{(0,2,\nu)}(t) = 0$ – otherwise; $u_{\nu j}^{(0,3)}(t) = 1$ at the moment when the A_{ν} is completed at time moment t and all other time moments till $t = T_f$, $u_{\nu j}^{(0,3)}(t) = 0$ – otherwise.

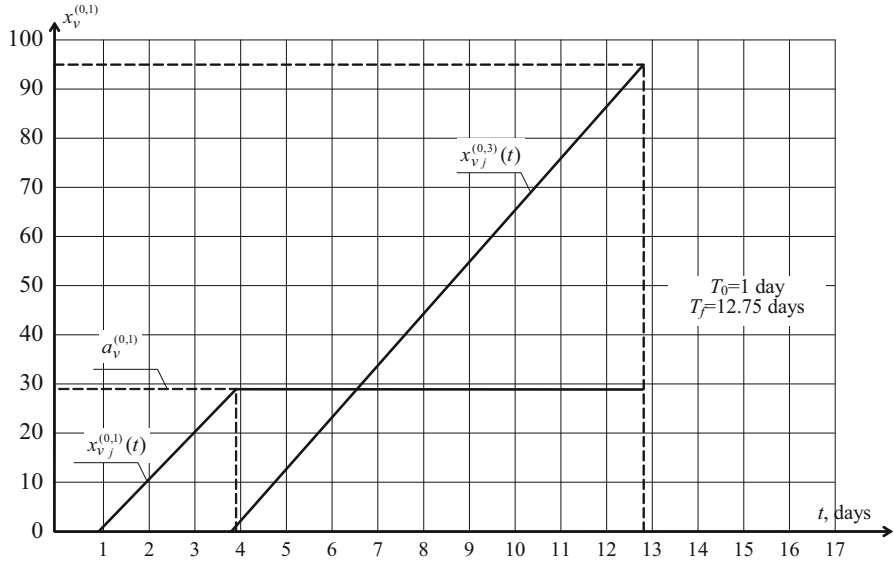


Fig. 7.2 Dynamics of job execution (Ivanov et al. 2016b)

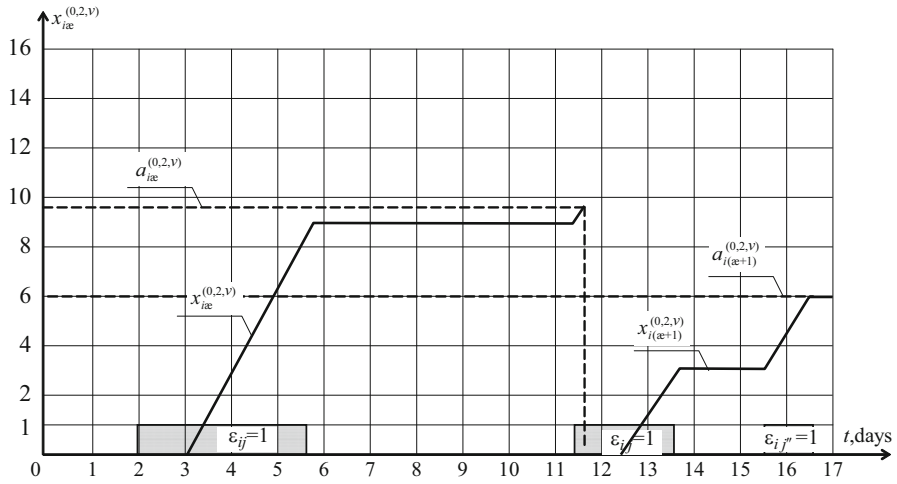


Fig. 7.3 Dynamics of operation execution (Ivanov et al. 2016a)

Equation (7.1) describes the process dynamics of operations execution for jobs A_v (see Figs. 7.2 and 7.3).

$x_{\nu}^{(0,1)} = \sum_{j=1}^m u_{\nu j}^{(0,1)}$ means that at each point in time where if $u_{\nu j}^{(0,1)}(t) = 1$, the

operations is being processed and its processed quantity increases. $x_{ie}^{(0,2,\nu)} = \sum_{j=1}^m \varepsilon_{ij}$

$(t)u_{iaej}^{(0,2,\nu)}$ means that processing is possible subject to feasible capacity time windows and $x_{\nu j}^{(0,3)} = u_{\nu j}^{(0,3)}$ means that if the job is completed the time to the end of the planning horizon elapses (i.e., earliness of the job completion subject to slack time).

In the example given in Fig. 7.2, it can be observed that for a planned batch of 29 units, the flow time of the job is 3 days (starting at $t = 1$ and ending at $t = 4$) and slack time is 8.75 days (subject to the due date 12.75 days).

Figure 7.3 depicts the execution dynamics of two subsequent operations at the i -supplier level subject to three capacity available time windows ($\varepsilon_{ij} = 1$). From Fig. 7.3, processing times, idle times, completion quantities and times can be observed.

Constraints (7.2) and (7.3) describe the precedence relations for jobs and operations of jobs. Constraint (7.4) is the assignment constraint and relates to splitting and overlapping. Equation (7.5) constrains the conditions for switching the control variables from 0 to 1.

The objective function $J_1^{(o)}$ (Eq. 7.7) characterizes the overall number of completed jobs at $t = T_f$. This is the performance indicator for *throughput*. $J_{<2,a,\nu>}^{(o)}$ (Eq. 7.8) reflects the flow time for A_{ν} . $J_3^{(o)}$ (Eq. 7.9) characterizes the *makespan* for all A_{ν} . $J_{<4,i,\nu>}^{(o)}$ (Eq. 7.10) characterizes the *lead-time* for A_{ν} . $J_{<5,i>}^{(o)}$ (Eq. 7.11) is the *waiting time* of job A_{ν} . $J_6^{(o)}$ (Eq. 7.12) characterizes the fullness of the job completion subject to the planned batch quantities at the end of the planning interval. $J_7^{(o)}$ (Eq. 7.13) expresses the *total tardiness* for all operations subject to penalty functions $\tilde{\beta}_{ie}^{(\nu)}$, i.e., *on-time-delivery*.

7.3.3 Dynamic Model of Channel Control (Model M_k)

A state of the channel $C_{\lambda}^{(i)}$ at B_i characterizes the readiness of the channel to process the operation $D_{\lambda e}^{(i,j)}$.

7.3.3.1 Process Model of Channel Control

$$x_{i\mathfrak{a}ej\lambda}^{(\kappa,1)} = \sum_{j'=1}^m \sum_{\mathfrak{a}'=1}^{s_j} \Theta_{i'\mathfrak{a}'j\mathfrak{a}} u_{i'\mathfrak{a}'j\lambda}^{(\kappa,1)} \frac{b_{i'\mathfrak{a}'i\mathfrak{a}}^{(j,\lambda)} - x_{i\mathfrak{a}ej\lambda}^{(\kappa,1)}}{x_{i'\mathfrak{a}'j\lambda}^{(\kappa,1)}} \quad (7.14)$$

$$x_{j\lambda}^{(\kappa,2)} = \sum_{i=1}^m \sum_{\mathfrak{a}=1}^{s_j} \left(u_{i\mathfrak{a}ej\lambda}^{(o,2)} + u_{i\mathfrak{a}ej\lambda}^{(\kappa,1)} \right) \quad (7.15)$$

7.3.3.2 Constraints

$$u_{i\mathfrak{a}ej\lambda}^{(0,2)} x_{i\mathfrak{a}ej\lambda}^{(\kappa,1)} = 0; \quad x_{i\mathfrak{a}ej\lambda}^{(\kappa,1)}(t) \in \{0, 1\} \quad (7.16)$$

$$\sum_{i=1}^n \sum_{\mathfrak{a}=1}^{s_j} u_{i\mathfrak{a}ej\lambda}^{(\kappa,1)}(t) \leq 1, \quad \forall j, \quad \forall \lambda \quad (7.17)$$

7.3.3.3 Start and End Conditions

$$h_0^{(\kappa)}(x^{(\kappa)}(T_0)) \leq \mathbf{0}; \quad h_1^{(\kappa)}(x^{(\kappa)}(T_f)) \leq \mathbf{0}. \quad (7.18)$$

7.3.3.4 Objective Functions

$$J_1^{(\kappa)} = \sum_{\Delta_1=1}^{m-1} \sum_{\Delta_2=\Delta_1+1}^m \sum_{\lambda=1}^l \sum_{\zeta=1}^l \int_{T_0}^{T_f} \left(x_{\Delta_1\lambda}^{(\kappa,2)}(\tau) - x_{\Delta_2\zeta}^{(k,2)}(\tau) \right) d\tau \quad (7.19)$$

$$J_2^{(\kappa)} = \sum_{\Delta_1=1}^{m-1} \sum_{\Delta_2=\Delta_1+1}^m \sum_{\lambda=1}^l \sum_{\zeta=1}^l \left(x_{\Delta_1\lambda}^{(\kappa,2)}(T_f) - x_{\Delta_2\zeta}^{(\kappa,2)}(T_f) \right) \quad (7.20)$$

7.3.3.5 Parameters

$b_{i'\mathfrak{a}'i\mathfrak{a}}^{(j,\lambda)}$ is the setup time of a channel

7.3.3.6 Decision Variables

- $x_{i\alpha j\lambda}^{(\kappa,1)}(t)$ is the state variable for the channel $C_\lambda^{(i)}$ at B_j during the setup to prepare the channel for processing $D_{\alpha'}^{(i,j)}$ after completion the operation $D_{\alpha}^{(i,j)}$
- $u_{i\alpha j\lambda}^{(\kappa,1)}(t)$ is a control variable; $u_{i\alpha j\lambda}^{(\kappa,1)}(t) = 1$, if $C_\lambda^{(i)}$ is in the setup process, $u_{i\alpha j\lambda}^{(\kappa,1)}(t) = 0$ otherwise
- $x_{j\lambda}^{(\kappa,2)}(t)$ is a state variable characterizing the process (run) time of a channel.

Equations (7.14) and (7.15) describe the dynamics of channel utilization. Equation (7.14) describes the setup dynamics and Eq. (7.15) considers the process time of each channel subject to assignments (i.e., variable $u_{i\alpha j\lambda}^{(o,2)} = 1$) given the operations control model M_o . Constraints (7.16) and (7.17) determine the setup sequence and conditions for setups at $C_\lambda^{(i)}$. Similar to the operations control model M_o , $h_0^{(\kappa)}$, $h_1^{(\kappa)}$ are known differential functions for start and end conditions for the state vector $x^{(\kappa)}$.

Objective functions (7.19) and (7.20) can be used to estimate the equality of channel utilization (e.g., as a requirement for equaling the loading of suppliers and their capacities subject to a supply chain collaboration agreement) at $t \in (T_0, T_f]$ and at the end of the planning interval.

7.3.4 Dynamic Model of Resource Control (Model M_r)

7.3.4.1 Process Model of Resource Control

$$x_{j\lambda\pi}^{(p,1)} = - \sum_{i=1}^m \sum_{\alpha=1}^{s_i} d_{i\alpha j\lambda}^{(\pi)} \left(u_{i\alpha j\lambda}^{(o,2)} + u_{i\alpha j\lambda}^{(\kappa,1)} \right) \quad (7.21)$$

$$x_{j\lambda\mu}^{(p,2)} = - \sum_{i=1}^m \sum_{\alpha=1}^{s_i} g_{i\alpha j\lambda}^{(\mu)} \left(u_{i\alpha j\lambda}^{(o,2)} + u_{i\alpha j\lambda}^{(\kappa,1)} \right) \quad (7.22)$$

$$x_{j\lambda\pi\eta}^{(p,1)} = - \sum_{i=1}^m \sum_{\alpha=1}^{s_i} d_{i\alpha j\lambda}^{(\pi)} \left(u_{i\alpha j\lambda}^{(o,2)} + u_{i\alpha j\lambda}^{(\kappa,1)} \right) + u_{j\lambda\pi(\eta-1)}^{(p,1)} \quad (7.23)$$

$$x_{j\lambda\mu\eta'}^{(p,2)} = - \sum_{i=1}^m \sum_{\alpha=1}^{s_i} g_{i\alpha j\lambda}^{(\mu)} \left(u_{i\alpha j\lambda}^{(o,2)} + u_{i\alpha j\lambda}^{(\kappa,1)} \right) + u_{j\lambda\mu(\eta'-1)}^{(p,2)} \quad (7.24)$$

$$x_{j\lambda\pi\eta}^{(p,3)} = u_{j\lambda\pi\eta}^{(p,1)}; \quad x_{j\lambda\mu\eta'}^{(p,4)} = u_{j\lambda\mu\eta'}^{(p,2)} \quad (7.25)$$

7.3.4.2 Constraints

$$\sum_{i, \mathfrak{a}, \lambda} d_{i\mathfrak{a}j\lambda}^{(\pi)} \left(u_{i\mathfrak{a}j\lambda}^{(o,2)} + u_{i\mathfrak{a}j\lambda}^{(\kappa,1)} \right) \leq \tilde{H}_j^{(\pi)}(t) \quad (7.26)$$

$$\sum_{i, \mathfrak{a}, \lambda} \int_{T_0}^{T_f} g_{i\mathfrak{a}j\lambda}^{(\mu)} \left(u_{i\mathfrak{a}j\lambda}^{(o,2)}(\tau) + u_{i\mathfrak{a}j\lambda}^{(\kappa,1)}(\tau) \right) d\tau \leq \int_{T_0}^{T_f} \tilde{H}_j^{(\mu)}(\tau) d\tau \quad (7.27)$$

$$u_{j\lambda\pi\eta}^{(p,1)} \left(a_{j\lambda\pi(\eta-1)}^{(p,3)} - x_{j\lambda\pi(\eta-1)}^{(p,3)} \right) = 0, \quad u_{j\lambda\pi\eta}^{(p,1)} x_{j\lambda\pi\eta}^{(p,1)} = 0 \quad (7.28)$$

$$u_{j\lambda\mu\eta}^{(p,2)} \left(a_{j\lambda\mu(\eta'-1)}^{(p,4)} - x_{j\lambda\mu(\eta'-1)}^{(p,4)} \right) = 0, \quad u_{j\lambda\mu\eta'}^{(p,2)} x_{j\lambda\mu\eta'}^{(p,2)} = 0 \quad (7.29)$$

$$u_{j\lambda\pi\eta}^{(p,1)}(t), u_{j\lambda\mu\eta}^{(p,2)}(t) \in \{0, 1\}, \quad \eta = 1, \dots, \tilde{\rho}_\lambda; \quad \eta' = 1, \dots, \tilde{\rho}_\lambda \quad (7.30)$$

7.3.4.3 Start and End Conditions

$$\mathbf{h}_0^{(r)} \left(\mathbf{x}^{(r)}(T_0) \right) \leq \mathbf{0} ; \quad \mathbf{h}_1^{(r)} \left(\mathbf{x}^{(r)}(T_f) \right) \leq \mathbf{0}. \quad (7.31)$$

7.3.4.4 Objective Function

$$J_{1j\pi}^{(p)} = \sum_{\lambda=1}^{l_j} \sum_{\eta=1}^{\tilde{\rho}_\lambda} x_{j\lambda\pi\eta}^{(p,3)}, \quad (7.32)$$

$$J_{2j\mu}^{(p)} = \sum_{\lambda=1}^{l_j} \sum_{\eta'=1}^{\tilde{\rho}_\lambda} x_{j\lambda\mu\eta'}^{(p,4)}, \quad (7.33)$$

7.3.4.5 Parameters

$d_{i\mathfrak{a}j\lambda}^{(\pi)}$, $g_{i\mathfrak{a}j\lambda}^{(\mu)}$ are given consumption rates of $\Phi S_\pi^{(j)}$ and $\Phi N_\mu^{(j)}$ for $D_\mathfrak{a}^{(i,j)}$ and $C_\lambda^{(j)}$. $\tilde{H}_j^{(\pi)}(t)$, $\tilde{H}_j^{(\mu)}(t)$ are known rates for recovery of $\Phi S_\pi^{(j)}$ and $\Phi N_\mu^{(j)}$ respectively. $a_{j\lambda\pi(\eta-1)}^{(p,3)}$, $a_{j\lambda\mu(\eta'-1)}^{(p,4)}$ are known volumes (quantities) of resource recovery at $(\eta-1)$ recovery cycle; $\tilde{\rho}_\lambda, \tilde{\rho}_\lambda$ are the numbers of total recovery cycles.

7.3.4.6 Decision Variables

$x_{j\lambda\pi}^{(p,1)}(t)$, $x_{j\lambda\mu}^{(p,2)}(t)$, $x_{j\lambda\pi\eta}^{(p,1)}(t)$, $x_{j\lambda\mu\eta}^{(p,2)}(t)$ are state variables that characterize the current quantity (volume) of:

1. non-storable resources $\Phi S_{\pi}^{(j)}$
2. storable resources $\Phi N_{\mu}^{(j)}$
3. non-storable and recoverable (at stages η and η') resources
4. storable and recoverable (at stages η and η') resources subject to channel $C_{\lambda}^{(j)}$

These state variables characterize π -resource dynamics, degradation and recovery.

$x_{j\lambda\pi\eta}^{(p,3)}(t)$, $x_{j\lambda\mu\eta}^{(p,4)}(t)$ are auxiliary state variables needed to define the sequence of resource replenishment and the ends of the replenishment intervals, respectively.

$u_{j\lambda\pi\eta}^{(p,1)}$, $u_{j\lambda\mu\eta}^{(p,2)}$ are control variables characterizing the recovery process for non-storable and storable resources, respectively; $u_{j\lambda\pi\eta}^{(p,1)}$, $u_{j\lambda\mu\eta}^{(p,2)}$ equal 1 if a π -resource is under recovery at t point of time, and equal 0 otherwise.

Equations (7.21), (7.22), (7.23), (7.24), and (7.25) describe the dynamics of resource consumption/degradation (Eqs. 7.21 and 7.22) and replenishment/recovery (Eqs. 7.23, 7.24, and 7.25) subject to assignment and setup decisions taken in models M_o and M_k .

According to constraints (7.26) and (7.27), if we have non-recoverable resources, $\tilde{H}_j^{(\pi)}$, $\tilde{H}_j^{(\mu)}$ are interpreted as maximal resource consumption intensities at each point of time t .

Constraints (7.28), (7.29), and (7.30) determine the sequence of replenishment/recovery actions. In other words, Eqs. (7.21), (7.22), (7.26), and (7.27) describe the process of resource decrease and Eqs. (7.23), (7.24), (7.25), (7.28), (7.29), and (7.30) describe the process of resource replenishment/recovery policies.

The objective functions (7.32) and (7.33) can be introduced to estimate the fullness of resource replenishment and the timeliness of resource replenishment, respectively. Equations (7.32) and (7.33) can also be used to estimate the time-to-recovery, i.e., the time needed for resource regeneration.

7.3.5 Dynamic Model of Flow Control (Model M_f)

The interrelations and mutual impacts of the assignment and flow control still remain an open research question. In the proposed approach, these decisions are considered simultaneously. Recall that lead-times (task times) may differ in terms of speeds $c_{i\alpha j\lambda\rho}^{(f,1)}$ and channel availabilities $\varepsilon_{ij}(t)$ and $\Theta_{i\alpha j\lambda}(t)$. For instance, the assignment of an operation to two different channels could result in a different execution control profile and task time. For this reason, the assignments from the

model $\mathbf{M}_o$ (made on the basis of the volumes $a_{i\mu}$) are now subject to further optimization in terms of flow dynamics control.

An assignment of an operation to a channel and the starting execution of the operations cause dynamic flows of processed products. Let us introduce a model for *flow dynamics control*.

7.3.5.1 Process Model of Flow Control

$$x_{i\alpha ej\lambda\rho}^{(f,1)} = u_{i\alpha ej\lambda\rho}^{(f,1)}; \quad x_{i\alpha ej\lambda\rho}^{(f,2)} = u_{i\alpha ej\lambda\rho}^{(f,2)} \quad (7.34)$$

7.3.5.2 Constraints

$$0 \leq u_{i\alpha ej\lambda\rho}^{(f,1)} \leq c_{i\alpha ej\lambda\rho}^{(f,1)} u_{i\alpha ej\lambda}^{(o,2)} \quad (7.35)$$

$$u_{i\alpha ej\lambda\rho}^{(f,2)} \left(a_{i\alpha\rho}^{(f,1)} - x_{i\alpha ej\lambda\rho}^{(f,1)} \right) = 0; \quad u_{i\alpha ej\lambda\rho}^{(f,2)} x_{i\alpha ej\lambda\rho}^{(o,2)} = 0; \quad u_{i\alpha ej\lambda\rho}^{(f,2)}(t) \in \{0, 1\} \quad (7.36)$$

$$\sum_{i=1}^m \sum_{\lambda=1}^{l_i} \sum_{\alpha=1}^{s_i} \sum_{\rho=1}^{k_i} x_{i\alpha ej\lambda\rho}^{(f,1)} \left(u_{i\alpha ej\lambda\rho}^{(o,2)} + u_{i\alpha ej\lambda\rho}^{(f,2)} \right) \leq \tilde{P}_j^{(1)} \quad (7.37)$$

$$\sum_{i=1}^m \sum_{\lambda=1}^{l_i} \sum_{\alpha=1}^{s_i} u_{i\alpha ej\lambda\rho}^{(f,1)} \leq \tilde{P}_{j\rho}^{(2)} \quad (7.38)$$

$$\sum_{\lambda=1}^{l_i} \sum_{\alpha=1}^{s_i} \sum_{\rho=1}^{k_i} u_{i\alpha ej\lambda\rho}^{(f,1)} \leq \tilde{P}_{ij}^{(3)} \quad (7.39)$$

7.3.5.3 Start and End Conditions

$$\mathbf{h}_0^{(f)} \left(\mathbf{x}^{(f)}(T_0) \right) \leq \mathbf{O} ; \quad \mathbf{h}_1^{(f)} \left(\mathbf{x}^{(f)}(T_f) \right) \leq \mathbf{O} \quad (7.40)$$

7.3.5.4 Objective Functions

$$J_2^{(f)} = \sum_{i=1}^m \sum_{\alpha=1}^{s_i} \sum_{\substack{j=1 \\ i \neq j}}^m \sum_{\lambda=1}^{l_i} \sum_{\rho=1}^{k_i} \left(a_{i\alpha\rho}^{(f,1)} - x_{i\alpha ej\lambda\rho}^{(f,1)} \right)^2 \bigg|_{t=T_f} \quad (7.41)$$

$$J_2^{(f)} = \sum_{i=1}^m \sum_{\mathfrak{x}=1}^{s_i} \sum_{\substack{j=1 \\ i \neq j}}^m \sum_{\lambda=1}^{l_i} \sum_{\rho=1}^{k_i} \int_{T_0}^{T_f} x_{i\mathfrak{x}j\lambda}^{(f,2)}(\tau) d\tau \quad (7.42)$$

7.3.5.5 Parameters

- $a_{i\mathfrak{x}\rho}^{(f,1)}$ is a known lot size of a product type ρ for each operation $D_{\mathfrak{x}}^{(i,j)}$;
- $\tilde{P}_j^{(1)}$, $\tilde{P}_{j\rho}^{(2)}$, $\tilde{P}_{ij}^{(3)}$ are known values for maximal storage capacity at B_j , handling capacity (throughput) at B_j for ρ , and handling capacity (throughput) between B_i and B_j ;
- $c_{i\mathfrak{x}j\lambda\rho}^{(f,1)}$ is maximal processing rate for the operation $D_{\mathfrak{x}}^{(i,j)}$ at the λ -channel; it determines the maximal possible value for $u_{i\mathfrak{x}j\lambda\rho}^{(f,1)}$.

7.3.5.6 Decision Variables

- $x_{i\mathfrak{x}j\lambda\rho}^{(f,1)}(t)$ is a state variable characterizing a quantity (volume) of the product « ρ » being delivered at B_j from B_i during the execution of $D_{\mathfrak{x}}^{(i,j)}$ (or the processed quantity at B_j , if $i = j$);
- $x_{i\mathfrak{x}j\lambda\rho}^{(f,2)}(t)$ is an auxiliary state variable characterizing total processing time (including waiting time) of a product flow ρ resulting from interaction of B_i and B_j for $D_{\mathfrak{x}}^{(i,j)}$ at $C_{\lambda}^{(i)}$, $C_{\lambda}^{(j)}$;
- $u_{i\mathfrak{x}j\lambda\rho}^{(f,1)}$ is a shipment rate for transportation from B_i to B_j (or processing rates at B_j if $i = j$); $u_{i\mathfrak{x}j\lambda\rho}^{(f,2)}(t)$ is auxiliary control variable; $u_{i\mathfrak{x}j\lambda\rho}^{(f,2)}(t)=1$, if processing at B_j is completed, $u_{i\mathfrak{x}j\lambda\rho}^{(f,2)}(t)=0$ – otherwise, or if after the completion of $D_{\mathfrak{x}}^{(i,j)}$ (or $D_{\mathfrak{x}}^{(i)}$, if $i = j$), the next operation in the technological process $D_{\mathfrak{x}}^{(i,j)}$ (or $D_{\mathfrak{x}}^{(i)}$, if $i = j$) begins.

Equation (7.34) describes the flow dynamics. Equations (7.35), (7.37), (7.38), and (7.39) constrain the maximal processing rates subject to assignments in the model $\mathbf{M}_{\mathbf{o}}$. Equation (7.15) considers the process time of each channel subject to assignments (i.e., variable $u_{i\mathfrak{x}j\lambda}^{(o,2)} = 1$) from the operations control model $\mathbf{M}_{\mathbf{o}}$. Constraints (7.16) and (7.17) determine the setup sequence and conditions for setups at $C_{\lambda}^{(i)}$. Similar to operations control model $\mathbf{M}_{\mathbf{o}}$, $\mathbf{h}_0^{(\kappa)}$, $\mathbf{h}_1^{(\kappa)}$ are known differential functions for start and end conditions for state vector $\mathbf{x}^{(\kappa)}$. Objective function (7.41) characterizes the fullness of the operations execution and is interconnected with the objective function (7.12) from $\mathbf{M}_{\mathbf{o}}$ model. Objective function (7.42) characterizes

waiting time for operations execution and is interconnected with the objective function (7.11) from $\mathbf{M}_o$.

7.3.6 Formulation of the Scheduling Problem

The models described above can be presented in an integrated form (model $\mathbf{M}$). As mentioned above, the model should provide decision makers with alternatives to handle. The performance indicators may be weighted in different proportions depending on the planning goals and operational strategies. The preference relations (minmax, maxmin, etc.) form the Pareto space and allow the calculation of a general relative quality index (7.43) within the corresponding schedule $\mathbf{u}(t)$.

$$\min \mathbf{J}(\mathbf{x}(t), \mathbf{u}(t), \xi(t), t) = \left\| \left(J_1^{(o)}, J_2^{(o)}, J_1^{(k)}, J_1^{(f)}, J_2^{(f)} \right)^T \right\|, \quad (7.43)$$

where $J_1^{(o)}, J_2^{(o)}, J_1^{(k)}, J_1^{(f)}, J_2^{(f)}$ are the values of the performance indicators.

For simplification, it is assumed that the transition from the vector form $\mathbf{J}$ to a scalar form J_G has been performed on the basis of weight coefficients.

Now the *scheduling problem* can be formulated as the following problem of dynamic system control (Ivanov et al. 2010). The task is to find a feasible control $\mathbf{u}(t)$, $[T_0, T_f]$ which ensures that the dynamic control model meets the constraint functions and guides the dynamic system (i.e., the schedule) $\mathbf{x} = \mathbf{f}(t, \mathbf{x}, \mathbf{u})$ from the initial state to the specified final state subject to given end conditions and the uncertainty area under the disturbances $\xi(t)$. If there are several feasible controls (schedules), then the best one (optimal) should be selected in order to maximize (minimize) the components of J_G .

7.3.7 Example

The original dynamic interpretation of the assignment of operations to a non-stationary set of machines can be exemplified in the following way. Consider four machines and six jobs $A^{(v)}$ each of which is composed of 3–6 operations $D_{\mathbf{a}}^{(i,j)}$. At each instant of time, only one operation can be processed on one machine (see Fig. 7.4).

Note that in this example, for simplification, we consider only a one-stage system with four alternative uniform suppliers. In the model, a multi-stage flow is considered as shown in Fig. 7.1. In Fig. 7.4, the execution dynamics of six jobs is presented for four time instants $t = t_1, t_2, t_3, t_f$. Different colors describe current execution states. The operations marked in black have already been completed. The operations marked in gray may be executed subject to the supplier availability and precedence relations. The operations marked in white cannot be executed yet

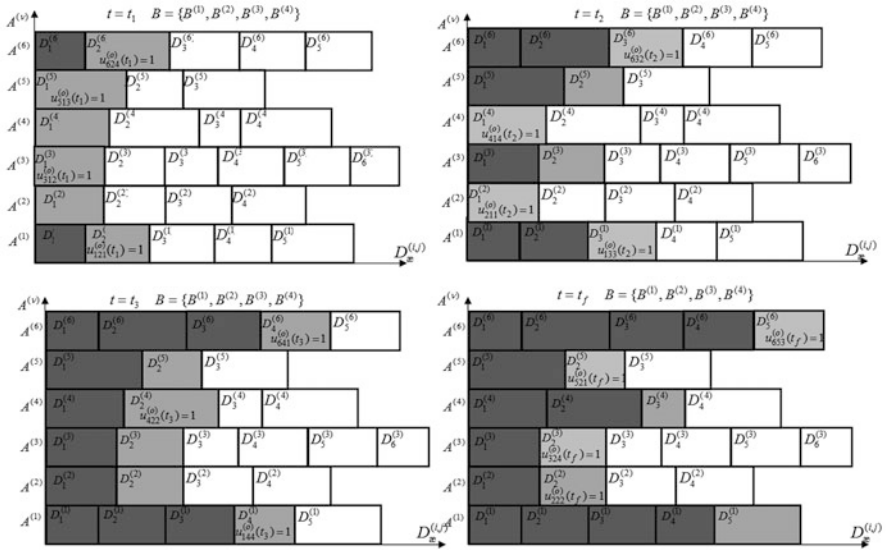


Fig. 7.4 Dynamic representation of the scheduling model (Adopted with changes from Ivanov et al. 2016b)

because of the precedence relations. For example, at $t = t_2$, the operation $D_2^{(4)}$ cannot be assigned since the operation $D_1^{(4)}$ is still being processed with the use of supplier $B^{(4)} \left(u_{414}^{(o)}(t_2) = 1 \right)$.

From Fig. 7.4, it can be observed that at each time instant, the assignment decisions consider only the gray colored operations subject to some available (“competing”) suppliers, i.e., the large-scale multi-dimensional combinatorial matrix is decomposed. The assignment of a supplier $B^{(j)}$ to the execution of the operation $D_{\alpha}^{(i,j)}$ can be described by the piecewise continuous function $u_{\nu \alpha j \lambda}^{(o)}(t)$ that becomes equal to 1 in the case of an operation assignment to a channel at a supplier or transportation link. These functions will play the role of optimal program control within the proposed dynamic model of operation execution and determine the optimal supply chain schedule, i.e., start and end time of operations, job and operation sequencing, and supplier assignments.

In the upper part of Fig. 7.4, suppliers $B^{(j)}$ are listed which are available at the current time instant. At $t = t_1, t_2, t_f$, the four suppliers $B^{(1)}, B^{(2)}, B^{(3)}, B^{(4)}$ are available. At $t = t_3$, only the three suppliers $B^{(1)}, B^{(2)}, B^{(4)}$ are available. This non-stationary set of supplier availability is represented in the model with the help of the preset matrix time function $\varepsilon_{ij}(t)$.

It can be observed from Fig. 7.4 that the current dimensionality of the considered scheduling problem for $t = t_1, t_2, t_3, t_f$ is determined by the dimensionality of the gray colored area. The operations in the black and white areas are not considered at the given time points and, therefore, will not influence the mathematical model for the assignment.

7.4 Modelling Capacity disruptions and Recovery

7.4.1 Assumptions and Notations

The following *general assumptions* are made (Ivanov et al. 2014):

- Problem settings and notations from Sect. 7.3 are used;
- Production and transportation capacities in the supply chain can be disrupted;
- The recovery actions are executed using different capacity recovery units;
- The capacity recovery units have unequal processing rates which may also differ for various operations and therefore influence the recovery time and recovered capacity volume;
- Each recovery action may be composed of functions from different capacity recovery units which are characterized by available time windows, productivity, i.e., the processed volume of recovery operations at an instant of time, and costs (fixed cost and variable recovery cost);
- Setup times for recovery operations are independent and included in the recovery time;
- Initial state and the desired end state of the supply chain schedule are known;
- Transition from the initial state to the end state depends on selection of controls in material flow (Sect. 7.3) and recovery scheduling models;
- Transition from the initial state to the end state can be affected by disruptions in supply chain capacities.

Denote $B^{(\nu,i)} = \{B_r^{(\nu,i)}; r = 1, \dots, \rho_\nu\}$ as a set of supply chain capacity recovery units, where r is a running number of capacity recovery units at a i -supplier in regard to a ν -job.

7.4.1.1 Parameters

- Denote $e_r^{(i)}, V_r^{(i)}, \Phi_r^{(i)}$ as maximal processing intensity of an operation at the supply chain capacity recovery unit $B_r^{(\nu,i)}$, maximal capacity of the supply chain capacity recovery unit $B_r^{(\nu,i)}$, and maximal productivity of the supply chain capacity recovery unit $B_r^{(\nu,i)}$ before the recovery correspondingly;
- $\bar{e}_r^{(i)}, \bar{V}_r^{(i)}, \bar{\Phi}_r^{(i)}$ are given variables characterizing the same parameters but after a disruption-driven recovery.
- Denote $S^{(\nu)} = \{S_l^{(\nu)}; l = 1, \dots, d_j\}$ as a set of recovery actions to execute operations $D^{(\nu)}$.
- Denote $F^{(\nu,l)} = \{F_\chi^{(\nu,l)}; \chi = 1, \dots, S_l\}$ as a set of functions of the supply chain capacity recovery unit to implement the recovery actions.
- Denote fixed cost as $c_{il}^{(\nu,1)}(t)$ and operative recovery cost as $c_{il}^{(\nu,2)}(t)$.

- Denote $g_l^{(\nu)}$ as a number of operations which may be re-stored by recovery action $S_l^{(\nu)}$.
- Denote $h_i^{(\nu)}$ as a given number of recovery actions $S_l^{(\nu)}$ which may be simultaneously used by the re-storing of an operation.
- Denote $D_{\chi}^{(\nu,i)} = \{D_{<l,\chi>}^{(\nu,i)}; l = 1, \dots, d_j, \chi = 1, \dots, S_l\}$ as a set of operations at supply chain capacity recovery units.
- Denote $D_r^{(p,i)} = \{D_{<r,k>}^{(p,i)}; p = 1, \dots, P^{(r)}; k = 1, \dots, \pi_i^{(r)}\}$ as a set of operations in the policies for capacity recovery units at $B_r^{(\nu,i)}$.
- Denote $V_{\chi}^{(\nu)}$ as the capacity of the supply chain recovery unit $B_r^{(\nu,i)}$ to execute the operation $D_{<l,\chi>}^{(\nu,i)}$ and $\delta_{\chi r}^{(\nu,l)}(\tau)$ as a quality function to estimate the recovery execution results.
- Denote $c_{\chi r}^{(l,1)}(\tau), c_{\chi r}^{(l,2)}(\tau)$ as given time functions of the fixed and operation costs of a supply chain capacity recovery unit $B_r^{(\nu,i)}$ used for the operation $D_{<l,\chi>}^{(\nu,i)}$ by realization of the function $F_{\chi}^{(\nu,l)}$.
- Denote $\eta_{il}^{(\nu)}(t)$ as a given time function which characterizes the costs of the idle time of channels in the supply chain for the operation $D_{\alpha}^{(i,j)}$;
- $y_{il}^{(\nu)}$ denotes the value of current idle cost due to a backlog in the operation $D_{\alpha}^{(i,j)}$ caused by unavailability of the recovery action $S_l^{(\nu)}$.

7.4.1.2 State Variables

$x_{il}^{(\nu)}(t)$ characterizes the execution of the operation $D_i^{(\nu)}$ with the use of the recovery action $S_l^{(\nu)}$,

$x_{il}^{(\nu,1)}(t)$ is an auxiliary variable characterizing the current state of the operation $D_i^{(\nu)}$.

Its value is numerically equal to the time interval that has elapsed since the beginning of the scheduling interval and the execution start of the operation $D_i^{(\nu)}$;

$x_{il}^{(\nu,2)}(t)$ is an auxiliary variable characterizing the current state of the processing operation. Its value is numerically equal to the time interval that has elapsed since the end of the execution of the operation $D_{\alpha}^{(i,j)}$ and the end of the scheduling interval;

$x_r^{(\nu,l)}$ is an auxiliary variable characterizing the employment time of the supply chain capacity recovery unit $B_r^{(\nu,j)}$;

$x_{\chi}^{(\nu,l)}$ is an auxiliary variable which characterizes the execution of the operation $D_{<l,\chi>}^{(\nu,j)}$;

$x_{rS_l}^{(\nu,l)}(t)$ is an auxiliary variable characterizing the current state of the processing operation. Its value is numerically equal to the time interval that has elapsed since the end of the execution of the operation $D_{<l,\chi>}^{(\nu,j)}$ and the instant of time t .

7.4.1.3 Decision Variables and Goals

$u_{il}^{(\nu)}(t)$ is a control that is equal to 1 if the operation $D_i^{(\nu)}$ is assigned to the recovery action $S_l^{(\nu)}$ at the moment t ; otherwise $u_{il}^{(\nu)}(t) = 0$.

$\vartheta_{il}^{(\nu,1)}(t)$ ($\vartheta_{il}^{(\nu,2)}(t)$) are auxiliary control variables that are equal to 1 if the operation $D_i^{(\nu)}$ has not started and is equal to 0 otherwise.

$w_{\chi r}^{(\nu,l)}$ is a control that is equal to 1 if the operation $D_{<l,\chi>}^{(\nu,j)}$ is assigned to the supply chain capacity unit $B_r^{(\nu,i)}$ and is equal to 0 otherwise;

$\omega_{rS_l}^{(\nu,l)}(t)$ is auxiliary control that is equal to 1 if all the operations $D_{<l,\chi>}^{(\nu,j)}$ in the function $F_{\chi}^{(\nu,l)}$ are completed and is equal to 0 otherwise;

$\vartheta_r^{(p,2)}(t)$ is the auxiliary control that is equal to 1 if the reconfiguration from old parameters $e_r^{(i)}, V_r^{(i)}, \Phi_r^{(i)}$ to new ones $\bar{e}_r^{(i)}, \bar{V}_r^{(i)}, \bar{\Phi}_r^{(i)}$ is completed and is 0 otherwise.

The *problem* is to find a joint schedule for the dynamic execution of the supply chain schedule and the recovery schedule of the destroyed capacities, i.e., the two schedules should be generated in a coordinated manner, i.e., including

- an optimal program control (schedule) for integrated execution of material flows at supply chain channels (model M1), and
- an optimal program control (schedule) for the recovery actions at capacity recovery units (model M2).

Jobs are to be scheduled subject to maximal customer service level (i.e., minimal lateness), minimal backlogs, minimal idle time at the supply chain channels and minimal costs of recovery actions (including, fixed, operation, and idle cost).

7.4.2 Mathematical Model M1

7.4.2.1 Process Model

$$\frac{dx_i^{(\nu,l)}}{dt} = \varepsilon_{il}(t) \cdot u_{il}^{(\nu)}(t); \quad \frac{dx_{il}^{(\nu,1)}}{dt} = \vartheta_{il}^{(\nu,1)}; \quad \frac{dx_{il}^{(\nu,2)}}{dt} = \vartheta_{il}^{(\nu,2)} \quad (7.44)$$

Equation (7.44) describes operation execution dynamics subject to the availability of the supply chain capacity recovery units described in the matrix function $\varepsilon_{il}(t)$. $u_{il}^{(\nu)}(t) = 1$ if the supply chain recovery action $S_l^{(\nu)}$ is assigned to the operation $D_i^{(\nu)}$, $u_{il}^{(\nu)}(t) = 0$ otherwise.

7.4.2.2 Constraints

$$\sum_{i=1}^{k_j} u_{il}^{(\nu)}(t) \leq g_l^{(\nu)}; \forall l; \sum_{l=1}^{d_j} u_{il}^{(\nu)}(t) \leq h_i^{(\nu)}; \forall i \quad (7.45)$$

$$\sum_{l=1}^{d_j} u_{il}^{(\nu)} \left[\sum_{\alpha \in \Gamma_{\nu 1}} (a_{\alpha}^{(\nu, l)} - x_{\alpha}^{(\nu, l)}) + \prod_{\beta \in \Gamma_{\nu 2}} (a_{\beta}^{(\nu, l)} - x_{\beta}^{(\nu, l)}) \right] = 0; \forall \nu \quad (7.46)$$

$$\vartheta_{il}^{(\nu, 1)} \cdot x_{il}^{(\nu, l)} = 0; \quad \vartheta_{il}^{(\nu, 2)} (a_{il}^{(\nu, l)} - x_{il}^{(\nu, l)}) = 0; \forall i; \forall l \quad (7.47)$$

$$u_{il}^{(\nu)}(t) \in \{0, 1\}; \vartheta_{il}^{(\nu)}(t) \in \{0, 1\} \quad (7.48)$$

Constraints (7.45) are assignment problem constraints. They define the possibilities of the parallel use of many recovery actions for one operation and for the parallel processing of many operations at one recovery action. Constraints (7.46) determine the precedence relations for recovery actions in a recovery policy. Constraints (7.47) interconnect main and auxiliary controls. Equation (7.48) constraints control to be Boolean variables.

7.4.2.3 End Conditions

$$t = t_0^{(j)} : x_i^{(\nu)}(t_0^{(j)}) = y_{il}^{(\nu)}(t_0^{(j)}) = x_{il}^{(\nu)}(t_0^{(j)}) = 0 \quad (7.49)$$

$$t = t_f^{(j)} : x_i^{(\nu)}(t_f^{(j)}) = a_i^{(\nu)}; y_l^{(\nu)}(t_f^{(j)}); x_i^{(\nu)}(t_f^{(j)}) \in \mathbf{R}^1 \quad (7.50)$$

Equations (7.49) and (7.50) define initial and end values of the variables $x_i^{(\nu)}(t)$, $y_{il}^{(\nu)}(t)$, $x_{il}^{(\nu)}(t)$ at the moments $t_0^{(j)}$ and $t_f^{(j)}$.

7.4.2.4 Objective Function

$$\min J_1^{(\nu)} = \sum_{i=1}^{k_v} \sum_{l=1}^{d_j} y_{il}^{(\nu)}(t_f^{(j)}) \quad (7.51)$$

$$\max J_2 = \sum_{i=1}^{k_\nu} \sum_{l=1}^{d_j} \frac{1}{x_{il}^{(\nu,2)}(t_f^{(j)})} \int_{t_0^{(j)}}^{t_f^{(j)}} g_{il}^{(\nu,2)}(\tau) d\tau \quad (7.52)$$

$$\min J_3 = \sum_{i=1}^{k_\nu} \sum_{l=1}^{d_j} \int_{t_0^{(j)}}^{t_f^{(j)}} \left[c_{il}^{(\nu,1)}(\tau) + c_{il}^{(\nu,2)}(\tau) \right] \cdot u_{il}^{(\nu)}(\tau) d\tau \quad (7.53)$$

Equation (7.51) minimizes losses from supply chain disruptions. Equation (7.52) estimates the service level by the volume of on-time completed jobs in the material flow. Equation (7.53) minimizes the total costs of the schedule recovery actions.

7.4.3 Mathematical Model M2

The *model of operation execution dynamics* at the capacity recovery units can be expressed as (7.54):

$$\frac{dx_{\chi}^{(\nu,l)}}{dt} = \sum_{r=1}^{\rho_\nu} u_{\chi r}^{(\nu,l)}; \quad \frac{dx_r^{(\nu,l)}}{dt} = \sum_{\chi=1}^{S_l} w_{\chi r}^{(\nu,l)}; \quad \frac{dx_{rS_l}^{(\nu,l)}}{dt} = \omega_{rS_l}^{(\nu,l)} \quad (7.54)$$

Equation (7.54) describes operations execution dynamic at the supply chain capacity recovery unit subject to the operation of the capacity recovery unit and recovery operations in the case of disruptions in the supply chain design structure.

The control actions are *constrained* as follows:

$$0 \leq u_{\chi r}^{(\nu,l)} \leq \left[e_{\chi r}^{(j)} \left(1 - g_r^{(p,2)}(t) \right) + \bar{e}_{\chi r}^{(j)} g_r^{(p,2)}(t) \right] w_{\chi r}^{(\nu,l)} \quad (7.55)$$

$$\sum_{\nu=1}^{n_j} \sum_{\chi=1}^{S_\nu} V_{\chi}^{(\nu)} \cdot w_{\chi r}^{(\nu,l)} \leq \left[V_r^{(j)} \left(1 - g_r^{(p,2)}(t) \right) + \bar{V}_r^{(j)} g_r^{(p,2)}(t) \right] \xi_r^{(j,1)} \quad (7.56)$$

$$\sum_{\nu=1}^{n_j} \sum_{\chi=1}^{S_\nu} u_{\chi r}^{(\nu,l)}(t) \leq \left[\Phi_r^{(j)} \left(1 - g_r^{(p,2)}(t) \right) + \bar{\Phi}_r^{(j)} g_r^{(p,2)}(t) \right] \xi_r^{(j,2)} \quad (7.57)$$

$$\sum_{r=1}^{\rho_\nu} w_{\chi r}^{(\nu,l)} \left[\sum_{\pi \in \Gamma_{\chi^3}} \left(a_{\pi}^{(\nu,l)} - x_{\pi}^{(\nu,l)} \right) + \prod_{\mu \in \Gamma_{\mu^4}} \left(a_{\mu}^{(\nu,l)} - x_{\mu}^{(\nu,l)} \right) \right] = 0 \quad (7.58)$$

$$\sum_{r=1}^{\rho_\nu} w_{\chi r}^{(\nu,l)}(t) \leq \psi_{\chi}; \forall \chi; \quad \sum_{\chi=1}^{S_l} w_{\chi r}^{(\nu,l)}(t) \leq \varphi_r; \forall r \quad (7.59)$$

$$\omega_{rS_l}^{(\nu,l)} \left(a_{S_l}^{(\nu,l)} - x_{S_l}^{(\nu,l)} \right) = 0; \quad (7.60)$$

$$w_{\chi r}^{(\nu, l)} \in \left\{0, u_{il}^{(\nu)}\right\}; \vartheta_r^{(p, 2)}(t), \omega_{r S_l}^{(\nu, l)} \in \{0, 1\}; \xi_r^{(j, 1)}(t); \xi_r^{(j, 2)}(t) \in [0, 1]. \quad (7.61)$$

With the help of functions $0 \leq \xi_r^{(j, 1)}(t) \leq 1$ и $0 \leq \xi_r^{(j, 2)}(t) \leq 1$, perturbation impacts at the capacity recovery unit $B_r^{(\nu, j)}$ can be modelled. Equations (7.55), (7.56), and (7.57) constraint processing at $B_r^{(\nu, j)}$ before and after the recovery. Constraints (7.58) set precedence relations on operations processing. Constraints (7.59) are related to the assignment problem. Equation (7.60) determines the conditions of processing completion.

7.4.3.1 End Conditions

$$t = t_0^{(j)} : x_{\chi}^{(\nu, l)}\left(t_0^{(j)}\right) = x_r^{(\nu, l)}\left(t_0^{(j)}\right) = x_{r S_l}^{(\nu, l)}\left(t_0^{(j)}\right) = 0; \quad (7.62)$$

$$t = t_f^{(j)} : x_{\chi}^{(\nu, l)}\left(t_f^{(j)}\right) = a_{\chi}^{(\nu, l)}; x_r^{(\nu, l)}\left(t_f^{(j)}\right); x_{r S_l}^{(\nu, l)}\left(t_f^{(j)}\right) \in \mathbf{R}^1. \quad (7.63)$$

7.4.3.2 Objective Function

$$J_4 = \sum_{r=1}^{\rho_{\nu}-1} \sum_{r_1=r+1}^{\rho_{\nu}} \int_{t_0^{(j)}}^{t_f^{(j)}} \left(x_r^{(\nu, l)}(\tau) - x_{r_1}^{(\nu, l)}(\tau)\right) d\tau; \quad (7.64)$$

$$J_5 = \sum_{r=1}^{\rho_{\nu}} \sum_{\chi=1}^{S_l} \int_{t_0^{(j)}}^{t_f^{(j)}} \delta_{\chi r}^{(\nu, l)}(\tau) \cdot w_{\chi r}^{(\nu, l)}(\tau) d\tau; \quad (7.65)$$

$$J_6 = \frac{1}{2} \sum_{\chi=1}^{S_l} \left(a_{\chi}^{(\nu, l)} - a_{\chi}^{(\nu, l)}\left(t_f^{(j)}\right)\right)^2. \quad (7.66)$$

$$J_7 = \sum_{\chi=1}^{S_l} \sum_{r=1}^{\rho_{\nu}} \int_{t_0^{(j)}}^{t_f^{(j)}} \left[c_{\chi r}^{(l, 1)}(\tau) + c_{\chi r}^{(l, 2)}(\tau)\right] w_{\chi r}^{(\nu, l)}(\tau) d\tau; \quad (7.67)$$

Equation (7.64) estimates uniformity of the use of supply chain capacity recovery units $B_r^{(\nu, j)}$ and $B_{r_1}^{(\nu, j)}$; $r, r_1 \in \{1, \dots, \rho_{\nu}\}$. Equation (7.65) estimates the amount of completed operations $D_{<l, \chi}^{(\nu, j)}$. Equation (7.66) takes into account losses from non-fulfilled operations. Equation (7.67) assesses the total costs of using the supply chain capacity recovery unit $B_r^{(\nu, j)}$.

7.4.4 Model Coordination

The developed modeling complex is composed of two dynamic control models subject to execution and recovery of material flows. Full consideration of the reconfiguration model can be found in (Ivanov and Sokolov 2013).

The presented models M1 and M2 are interconnected with the help of Eq. (7.47), where elements from M2 are used in M1. In its turn, M1 influences M2 through Eqs. (7.55) and (7.60).

The proposed models and algorithms have been validated in a developed prototype based on C++ and XML. The optimal program control calculation is based on the *Hamiltonian* function. In integrating the main and the conjunctive equation systems, the values of the variables in both of the systems can be obtained at each point in time. The maximum principle guarantees that the optimal solution (i.e., the solution with maximal values) of the instantaneous problems (i.e., at each point of time) give the optimal solution to the overall problem. For these sub-problems, optimal solutions can be found, e.g., with the help of mathematical programming. Then these solutions are linked into an optimal program control.

7.5 Computational Procedure

7.5.1 Transformation of the Optimal Control Program to the Boundary Problem

Consider the relations between the models from Sect. 7.3 (Fig. 7.5) including several perturbation vectors $\xi(t)$.

According to the problem statement (see Fig. 7.1), we extend now the models described in Sect. 7.3 by introduction of uncertainties in capacities and supply. Model $M_o(\xi^o)$ of operations control is subject to uncertainty in channel availability $\Theta_{ievj\lambda}(t)$ (Eq. 7.1) that may influence customer order fulfillment dynamics. Model $M_k(\xi^k)$ of channel control describes capacity degradation and recovery dynamics at production machines and transportation means in regard to Eqs. (7.16) and (7.17). Model $M_r(\xi^r)$ of resource control considers material supply dynamics and describes supply degradation and recovery dynamics subject to the right-hand parts of Eqs. (7.26) and (7.27). Model $M_f(\xi^f)$ of flow control depicts uncertainties in processing and shipment dynamics subject to disruption and recovery in storage capacity at B_j , handling capacity (throughput) at B_j for product p , and handling capacity (throughput) between B_i and B_j in regard to Eqs. (7.37), (7.38), and (7.39).

The scheduling model in terms of optimal program control may be represented in the form of Eq. (7.68):

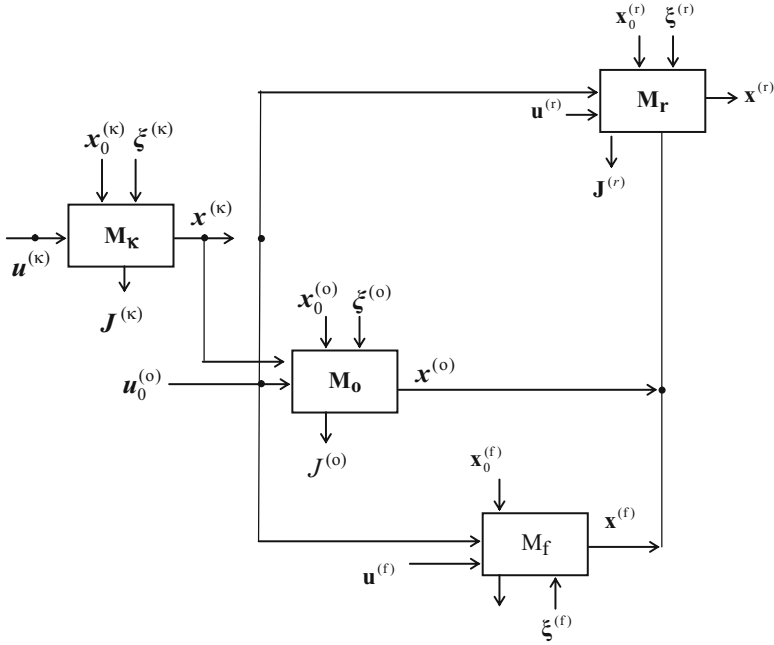


Fig. 7.5 Model integration and introduction of uncertainty

$$M = \begin{cases} \mathbf{u}(t) \mid \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t), \\ \mathbf{h}_0(\mathbf{x}(T_0)) \leq 0, \quad \mathbf{h}_1(\mathbf{x}(T_f)) \leq 0, \\ \mathbf{q}^{(1)}(\mathbf{x}, \mathbf{u}) = 0, \quad \mathbf{q}^{(2)}(\mathbf{x}, \mathbf{u}) \leq 0, \end{cases} \quad (7.68)$$

where $\mathbf{h}_0$, $\mathbf{h}_1$ are given functions of end conditions at time $t = T_0$, $t = T_f$ and $\mathbf{q}^{(1)}$, $\mathbf{q}^{(2)}$ is the generalized notation of the linear and non-linear constraints, respectively. The models presented have four features that *distinguish them from classical optimal control problems*. First, the right parts of differential equations in $\mathbf{M}_O$ model are broken not only during the assignment selections, but also at the beginning of transportation operations. Second, we consider a multi-objective formulation. Third, perturbations (disturbances) are considered in different models. Fourth, and probably, the most important, non-linearity is transferred to the constraints; therefore, process control models are linear (apart from flow and channel control models that are bi-linear).

In this setting, at the moment $t = T_0$ we have some start conditions $\mathbf{h}_0(\mathbf{x}(t)) \in R^{\tilde{m}_G}$ and it becomes possible to find both optimal program control vector $\mathbf{u}^*(t)$ and state vector $\mathbf{x}^*$ at $t = T_0$. Assuming that partial objective functions can be converted to a general performance indicator J_G , we have:

$$J_G = \tilde{\lambda}_1 \phi_G \mathbf{x}(T_f) + \tilde{\lambda}_2 \int_{T_0}^{T_f} f_G^{(1)}(\mathbf{x}(\tau)) d\tau + \tilde{\lambda}_3 \int_{T_0}^{T_f} f_G^{(2)}(\mathbf{u}(\tau)) d\tau, \quad (7.69)$$

where $\tilde{\lambda} > 0$ are given weight coefficients, $\phi_G, f_G^{(1)}, f_G^{(2)}$ are given functions at $X \subseteq \mathbb{R}^{n_G}, X \times T, U \subseteq \mathbb{R}^{m_G}$ ($T = \mathbb{R}^+$ is the set of time moments, $\mathbb{R}^+$ is a set of real numbers, X, U are sets for $\mathbf{x}, \mathbf{u}$). Assume that $\phi_G(\mathbf{x})$ has no interruptions for $X, f_G^{(1)}(\mathbf{x}(\tau), \tau)$, along with its derivative for $\mathbf{x}$ at each $\tau \in (T_0, T_f]$, has no interruptions for $\mathbf{x}$ and is piecewise-continuous at $\mathbf{x} \in X$ for $\tau; f_G^{(2)}$ for each τ is convex regarding $\mathbf{u}$ and for each $\mathbf{u} \in U$ it is bounded and piecewise-continuous for t . In the model $\mathbf{M}$ we consider, along with the feasible control class $\tilde{K}$ and extended feasible control class $\tilde{\tilde{K}}$, where the relay condition (Eq. 7.70)

$$u_{\nu\alpha j}^{(o)}(t) \in \{0; 1\} \quad (7.70)$$

is replaced by a less strict one (Eq. 7.71)

$$u_{\nu\alpha j}^{(o)}(t) \in [0; 1] \quad (7.71)$$

In this case, an extended domain $\tilde{\tilde{Q}}(\mathbf{x}(t))$ of feasible control inputs may be formed by means of special transformations ensuring the convexity and the compactness of $\mathbf{Q}(\mathbf{x}(t))$ (Ivanov et al. 2010).

Remark Note that the constraints (7.2), (7.3), (7.4), (7.5), (7.35), (7.36), (7.37), (7.38), and (7.39) are identical to those in discrete optimization models for scheduling. However, at each t -point of time, the number of variables in the calculation procedure is determined by the operations which are currently in the “active zone” of scheduling (Ivanov et al. 2016). For the problem sizes subject to the “active zone” known methods for the solution of discrete optimization methods (e.g., the Hungarian method for $\mathbf{M}_o$ or linear programming L for $\mathbf{M}_f$) can be applied.

7.5.2 Hamiltonians

The computational procedure for the developed model is based on the integration of the main and conjunctive equation systems subject to the maximization of the following Hamiltonian (7.72), (7.73), and (7.74):

$$H(\mathbf{x}^*(t), \mathbf{u}^*(t), \boldsymbol{\psi}(t)^*) = \max_{\tilde{\tilde{\mathbf{u}}} \in \tilde{\tilde{Q}}}(\mathbf{x}) \sum_{z=1}^2 H_l(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\psi}(t)), \quad (7.72)$$

$$H_1 = \sum_{\nu=1}^n \sum_{\mathfrak{x}=1}^{s_j} \sum_{j=1}^m \left[\psi_{\nu\mathfrak{x}}^{(o)} \cdot \varepsilon_{\nu j} + \psi_j^{(k)} + w_2^{(o)} \tilde{\beta}_{\nu\mathfrak{x}j}^{(o)} \right] u_{\nu\mathfrak{x}j}^{(o)}, \quad (7.73)$$

$$H_2 = \sum_{\nu=1}^n \sum_{\mathfrak{x}=1}^{s_j} \sum_{j=1}^m \left[\psi_{\nu\mathfrak{x}j}^{(f)} + w_5^{(f)} \tilde{\beta}_{\nu\mathfrak{x}}^{(f)} \right] u_{\nu\mathfrak{x}j}^{(f)}, \quad (7.74)$$

where $\boldsymbol{\psi}(t)$ is the conjunctive vector.

The maximization of the Hamiltonian H_1 for process model of operation execution control in combination with the respective constraints solves the assignment problem. The maximization of the Hamiltonian H_2 for flow control model in combination with the respective constraints solves the linear programming problem.

At each instant of time, only those jobs and constraints from the “active scheduling zone” (i.e., the area marked in gray in Fig. 7.4) are considered in the models $\mathbf{M}_o$ and $\mathbf{M}_f$ which meet the precedence constraints. By a dynamic switching of the precedence constraints from inequalities to equalities, the size of the scheduling problem at each time point is reduced. The Hamiltonians (7.73) and (7.74) can be maximized when the precedence constraints satisfy the corresponding variables $u_{\nu\mathfrak{x}j}^{(o)}$ and $u_{\nu\mathfrak{x}j}^{(f)}$. In this case, only a part of the precedence constraints is considered for the current assignment problem since, when the control is switched to zero in the operation execution control model, it becomes active in the right-hand part of the precedence constraints in the flow control model. Therefore, the reduction of problem dimensionality at each instant of time in the calculation process is ensured because of the recurrent operation description.

As the dynamics of the state and conjunctive variables $\mathbf{x}(t)$ and $\boldsymbol{\psi}(t)$ is described by the differential equations, it becomes possible to calculate $\mathbf{x}(t)$ and $\boldsymbol{\psi}(t)$ at any instant of time subject to the given initial conditions $(\mathbf{x}_0, \boldsymbol{\psi}_0)$. The Hamiltonian (7.72) turns into a function of only one variable $\mathbf{u}(t)$ that can be calculated at any t subject to $\mathbf{u}(t) \in Q_u$. Therefore, the *scheduling problem* can be reduced to a two-point boundary problem with the help of the local cut method (Boltyanskiy 1973). The proof is complete.

7.5.3 Conjunctive System and Transversality Conditions

A methodical challenge in applying the maximum principle is to find the coefficients of the conjunctive system which change in dynamics. One of the contributions of this paper is that these coefficients can be found analytically from Eqs. (7.76) and (7.77). The coefficients of the conjunctive system play the role of dynamical Lagrange multipliers as compared with mathematical programming dual formulations.

The *conjugate system* can be written as follows (Boltyanskiy 1973; Moiseev 1974):

$$\psi_{\tilde{i}} = -\frac{\partial H}{\partial x_{\tilde{i}}} + \sum_{\alpha=1}^{\tilde{I}_1} \delta_{\alpha}^{\sim}(t) \frac{\partial \mathbf{q} \tilde{\alpha}^{(1)}(\mathbf{x}(t), \mathbf{u}(t))}{\partial x_{\tilde{i}}} + \sum_{\beta=1}^{\tilde{I}_2} \rho_{\beta}^{\sim}(t) \frac{\partial \mathbf{q}_{\beta}^{(2)}(\mathbf{x}(t), \mathbf{u}(t))}{\partial x_{\tilde{i}}}. \quad (7.75)$$

The coefficients $\delta_{\alpha}^{\sim}(t)$, $\rho_{\beta}^{\sim}(t)$ can be determined by means of the following expressions (7.76) and (7.77):

$$\rho_{\beta}^{\sim}(t) \mathbf{q} \tilde{\beta}^{(2)}(\mathbf{x}(t), \mathbf{u}(t)) \equiv 0, \quad \tilde{\beta} \in \{1, \dots, \tilde{I}_2\}, \quad (7.76)$$

$$\begin{aligned} \text{grad}_{\mathbf{u}} H(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\psi}(t)) &= \sum_{\alpha=1}^{\tilde{I}_1} \delta_{\alpha}^{\sim}(t) \text{grad}_{\mathbf{u}} \mathbf{q} \tilde{\alpha}^{(1)}(\mathbf{x}(t), \mathbf{u}(t)) \\ &\quad + \sum_{\beta=1}^{\tilde{I}_2} \rho_{\beta}^{\sim}(t) \text{grad}_{\mathbf{u}} \mathbf{q} \tilde{\beta}^{(2)}(\mathbf{x}(t), \mathbf{u}(t)). \end{aligned} \quad (7.77)$$

In the Eqs. (7.75), (7.76), and (7.77), $x_{\tilde{i}}$ are the elements of the general state vector $\mathbf{x}(t)$ and $\boldsymbol{\psi}(t)$ are the elements of the conjugate vector $\boldsymbol{\psi}(t)$. In accordance with the maximum principle, the conjugate system can be written as Eqs. (7.78), (7.79), and (7.80):

$$\frac{d\psi_{v\alpha j}^{(o)}}{dt} = \psi_{v\alpha j}^{(o)} = \sum_{j=1}^m \left[\psi_{v(\alpha+1)}^{(o)} \varepsilon_{vj} + \psi_j^{(k)} + \lambda_2^{(o)} \alpha_{v(\alpha+1)j}^{(o)} \right] u_{v(\alpha+1)j}^{(o)}, \quad (7.78)$$

$$\frac{d\psi_j^{(k)}}{dt} = \psi_j^{(k)} = 0, \quad (7.79)$$

$$\frac{d\psi_{v\alpha j}^{(f)}}{dt} = \psi_{v\alpha j}^{(f)} = 0. \quad (7.80)$$

The *transversality conditions* can be formulated as shown in Eqs. (7.81), (7.82), and (7.83):

$$\psi_{v\alpha}^{(o)}(T_f) = \lambda_1^{(o)} \left(a_{v\alpha}^{(o)} - x_{v\alpha}^{(o)}(T_f) \right); \quad (7.81)$$

$$\psi_j^{(k)}(T_f) = \lambda_3^{(k)} \left(T - x_j^{(k)}(T_f) \right); \quad (7.82)$$

$$\psi_{v\alpha j}^{(f)}(T_f) = \lambda_5^{(f)} \left(a_{v\alpha j}^{(f)} - x_{v\alpha j}^{(f)}(T_f) \right); \quad (7.83)$$

7.5.4 Computational Algorithm

Let us consider the algorithmic realization of the above-described modified maximum principle. After transforming it into a boundary problem, a relaxed problem can be solved to receive an optimal program control, the computation of which the main

and conjunctive systems are integrated, i.e., the optimal program control vector $\mathbf{u}^*(t)$ and the state trajectory $\mathbf{x}^*(t)$ are obtained. The optimal program control vector at time $t = T_0$ returns the maximum to objective functions, which have been transformed to a general performance index and expressed in scalar form J_G .

The basic peculiarity of the boundary problem considered is that the initial conditions for the conjunctive variables $\psi(t_0)$ are not given. At the same time, optimal program control should be calculated subject to start and end conditions. To obtain the conjunctive system vector, we use the Krylov–Chernousko method of successive approximations (MSA) for an optimal program control problem with a free right end which is based on the joint use of a modified successive approximation method (Krylov and Chernousko 1972). We propose using a heuristic schedule $\bar{\mathbf{u}}(t)$ to obtain the initial conditions for $\psi(t_0)$. Then, the algorithm can be stated as follows:

Step 1 An initial solution $\bar{\mathbf{u}}(t)$, $t \in (T_0, T_f]$ (a feasible schedule) is selected and $r = 0$.

Step 2 As a result of the dynamic model run, $\mathbf{x}^{(r)}(t)$ is received. In addition, if $t = T_f$ then the record value $J_G = J_G^{(r)}$ can be calculated. Then, the transversality conditions are evaluated.

Step 3 The conjugate system is integrated subject to $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$ and over the interval from $t = T_f$ to $t = T_0$. Here, the iteration number $r = 0$ is completed.

Step 4 From the time point $t = T_0$ onwards, the control $\mathbf{u}^{(r+1)}(t)$ is determined ($r = 0, 1, 2, \dots$ denotes the number of the iteration). In parallel with the maximization of the Hamiltonian, the main system of equations and the conjugate one are integrated. The maximization involves the solution of several mathematical programming problems at each time point.

In the result, the assignment of jobs to suppliers and the definition of the start and end time for processing an operation on the channels at the supplier results automatically from the optimal program control vector $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$ subject to the assignment control variables. The assignments (i.e., the control variables $u_{i \in j \lambda}^{(o, 2, \nu)}(t)$) from the model $\mathbf{M}_o$ are used in the channel control model $\mathbf{M}_k$, resource control model $\mathbf{M}_r$ and flow control $\mathbf{M}_f$ by means of the constraints (7.16), (7.26), (7.27), (7.35), (7.36), and (7.37) respectively. At the same time, the model $\mathbf{M}_f$ influences the model $\mathbf{M}_o$ through the transversality conditions, the conjunctive system, and the Hamiltonian function. In addition, the possible resource structure dynamics and flow control dynamics through perturbation impacts can be taken into account including some perturbation vectors $\xi(t)$ in supply constraints (7.26) and (7.27) and capacity constraints (7.37), (7.38), and (7.39).

In each iteration, the main part of the functional J_G is negative and has a maximal absolute value among the main parts of the increments computed for all possible variations of the control variables. In contrast to gradient methods and classical formulas of calculus of variations, it is sufficient to use the smallness of the integral increment norm $\|\delta \mathbf{u}\|$ for decreasing J_G . The smallness $\|\delta \mathbf{u}\|$ at the planning interval $\sigma = (T_o, T_f]$ is not necessary. The advantage of MSA is that it allows implementation of *needle control variations* subject to the whole area of feasible control actions

subject to the given constraint system, i.e., the area of feasible schedules. Another MSA advantage is that the search for an optimal control in each iteration is performed in the class of boundary (e.g., pointwise or relay) functions which correspond to the discrete nature of decision making in scheduling.

Note that the MSA in its initial form has not guaranteed the convergence. By now, a number of MSA modifications with proved convergence exist (Lyubushin 1979). The following MSA modification can be used for the scheduling algorithm considered. In step 4, Eq. (7.84) is used for maximization of the Hamiltonian:

$$u^{(r+1)}(t) = \begin{cases} Ru^{(r)}(t), t \in [t', t''] \\ u^{(r)}(t), t \notin [t', t''] \end{cases}, \quad (7.84)$$

where $[t', t'']$ is selected so that a decrease

$$J_G^{(r+1)} < J_G^{(r)} \quad (7.85)$$

is ensured.

$J_G^{(r)}$, $J_G^{(r+1)}$ are the values of the goal functional subject to $\mathbf{u}^{(r)}$, $\mathbf{u}^{(r+1)}$, respectively. In Eq. (7.84), the operator R corresponds to step 4 of the DYN algorithm. The selection of t', t'' in each iteration is based on the values of the Hamiltonian functions of two subsequent iterations. An example is provided in Fig. 7.6.

At the Y-axis, the values of the Hamiltonian function (7.72) are presented. The X-axis represents the instants of the time interval $[0, 29]$. The three lines correspond to three computational iterations and depict the values of the Hamiltonian function (19) at different instants of time. The red line (starting at $t = 0$ with the value 500) references the first iteration; the blue line (starting at $t = 0$ with the value 550) references the second iteration; and the green line (starting at $t = 0$ with the value 650) references to the third iteration. It can be observed that within $t \in [0, 12]$, the schedule calculated at the third iteration provides better results. For instance, H_1 (Eq. 7.73) increases in the case of lower penalties. Similarly, H_2 (Eq. 7.74) increases in the case of higher values of $u_{ij}^{(f)}$, which means a higher volume of processed goods.

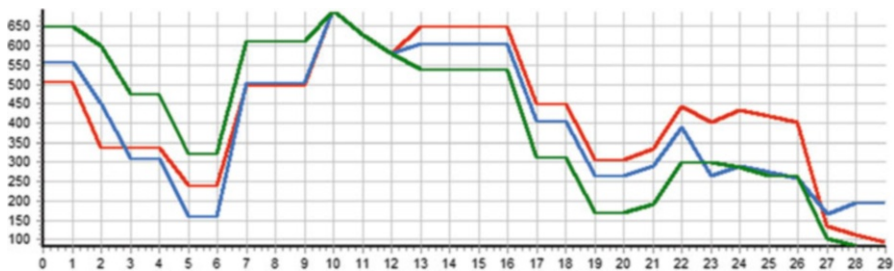


Fig. 7.6 Hamiltonian function values in different iterations

However, within $t \in [12, 27]$, the first scheduling iteration outperforms the other iterations. For $t \in [27, 29]$, the third iteration does not improve the results of the second iteration, i.e., the schedule of the second iteration for $t \in [27, 29]$ is used. In combining the *upper bounds* of the Hamiltonian functions, an optimal schedule is calculated. It contains, for this example, the results of the third iteration (green line) for $t \in [0, 12]$, the first iteration (red line) for $t \in [12, 27]$, and the second iteration (blue line) for $t \in [27, 29]$.

The dynamic coordination parameters are conjunctive variables which change their values during the iterative process of the corresponding two-point boundary problem solution. At each instant of time, the global objective function is Hamiltonian (7.72). The locally coordinated sub-problems are partial combinatorial assignment problems and linear programming problems, which are formed dynamically in dependence on the current active scheduling zone (see Fig. 7.4).

If so, the values of the conjunctive variables (i.e., the coordinated signals) change from one iteration to the next iteration and can be considered in some sense as a generalization of the coordination parameters previously considered in the decomposition–coordination procedures of Dantzig and Wolfe (1960) (goal coordination) and Kornai and Lipták (1965) (resource coordination). In the proposed approach, the conjunctive variables and the Hamiltonian function allow at each instant of time to perform both the goal and the resource coordination of the solutions which are found in the combinatorial sub-problems.

In addition, the developed modification of the MSA method guarantees a monotonic change of the conjunctive variable values by both the transversality conditions (7.81), (7.82), and (7.83) and a situational selection of the Hamiltonian function values. The transversality conditions interconnect state parameter values in the main and conjunctive systems at the moment in time that corresponds to the end of the planning interval. The values of the Hamiltonian function (7.72) are saved during the iterative search procedure (cf Fig. 7.6). The theoretical convergence of the considered iterative procedure has been previously proved in Lyubushin (1979) and Chernousko and Lyubushin (1982).

Finally, we note the problem with operation preemptions while applying the algorithm described above. Since operations have different processing durations, the machines become available for the processing of the next operations at different points of time. This can result in a situation where the Hamiltonian maximization can lead to an improvement in objective functions if operation processing at one machine is interrupted and the operation is re-assigned to the new machine that has become available. In some practical problems, it can be allowed in technology. In other settings, such preemptions can be prohibited. The study by Ivanov et al. (2014) showed how this problem can be resolved at the modelling and algorithmic levels. The monotonous and convergence of the modified successive approximations method for problems with a non-preemptive condition has been previously proved for two-point linear boundary problems with convex control area and goal function.

7.6 Optimality and Complexity Analysis

7.6.1 Optimality and Existence Analysis

7.6.1.1 Proposition 1

The optimal program control $\mathbf{u}(t)$ is an optimal supply chain schedule.

7.6.1.2 Existence Proof

The formulated model is a linear, non-stationary, finite-dimensional controlled system of differential equations with a convex area of feasible control. This model form satisfies the conditions of the existence theorem in Lee and Markus (1967, Theorem 4, Corollary 2), which allows us to assert the existence of an optimal solution in the appropriate class of feasible controls. According to Lee and Markus (1967, Theorem 4, Corollary 2), along with the initial class $\tilde{K}$ formed via the constraints $\mathbf{q}^{(1)}$ and $\mathbf{q}^{(2)}$ describing the domain $\mathbf{Q}(\mathbf{x}(t))$, an extended class $\tilde{\tilde{K}}$ of control inputs can be considered. In the extended class $\tilde{\tilde{K}}$, the relay constraints $u_{v\bar{a}ej}^{(o)}(t) \in \{0; 1\}$ are substituted by a less strict one $u_{v\bar{a}ej}^{(o)}(t) \in [0; 1]$ ($\mathbf{u}$ is substituted by $\tilde{\mathbf{u}}$). In this case, an extended domain $\tilde{\tilde{\mathbf{Q}}}(\mathbf{x}(t))$ of feasible control inputs may be formed by means of special transformations ensuring the convexity and the compactness of $\mathbf{Q}(\mathbf{x}(t))$ (Moiseev 1974). The theorem of Lee and Markus (1967) confirms that all the conditions for the existence of an optimal control for the extended control class $\tilde{\tilde{K}}$ are valid. If in a given class of feasible control actions $\tilde{\tilde{K}}$, an optimal control $\tilde{\mathbf{u}}(t)$ exists. Then, as arises from the local cut method, the control $\tilde{\mathbf{u}}(t)$ returns at each instant of time $t \in (T_0, T_f]$ at the set $\tilde{\tilde{\mathbf{Q}}}(\mathbf{x}(t))$ the maximum to the Hamiltonian (7.72), (7.73), and (7.74). The proof is complete.

7.6.1.3 Optimality Proof

An analysis of (7.72), (7.73), and (7.74) shows that the Hamiltonian is linear in $\tilde{\mathbf{u}}$. Since $\tilde{\tilde{\mathbf{Q}}}(\mathbf{x}(t))$ is a linear capsule of $\mathbf{Q}(\mathbf{x}(t))$, the maximization of the Hamiltonian (19)–(21) over the sets $\mathbf{Q}$ and $\tilde{\tilde{\mathbf{Q}}}$ leads to the same results. An optimal control for the class $\tilde{K}$ belongs to the class $\tilde{\tilde{K}}$. Taking into account $\tilde{K} \subset \tilde{\tilde{K}}$, this control is also optimal for the class $\tilde{K}$. Therefore, the relaxed problem can be solved instead of the initial one to obtain an optimal feasible control for the class $\tilde{K}$. The proof is complete.

Corollary 2 An analysis of the studies (Boltyanskiy 1973; Moiseev 1974) shows that for a linear, non-stationary, finite-dimensional system (model $\mathbf{M}$) with a

convex area of a feasible control $Q(x)$ and the goal vector, the stated necessary optimality conditions are also sufficient conditions.

7.6.2 Analysis of the Algorithm Complexity

It is known from the literature that the MSA method can be easily implemented when programming an algorithm. It also facilitates fast computation. One MSA iteration corresponds to one iteration of a gradient method. The MSA differs from the gradient methods in calculating the Hamiltonian function (7.72) in each iteration with the usage of previous iteration data.

7.6.2.1 Proposition 2

The computational complexity of the MSA in one iteration is polynomial. With regard to the considered scheduling problem, the complexity of the proposed algorithm in one iteration is determined by the complexity of the IP assignment problem and the LP problem.

7.6.2.2 Proof

On the basis of the works on the Hungarian method, the *complexity of the integer programming problem* can be estimated according to Eq. (7.86)

$$O(\bar{m}_1^3) \left(\frac{\sigma}{\Delta t} \right), \quad (7.86)$$

where

$O(\bar{m}_1) = \frac{11\bar{m}_1^3 + 12\bar{m}_1^2 + 3\bar{m}_1}{6}$ is the maximal number of the “+” operations at one time point of the planning period $(T_o, T_f]$ for the assignment problem being solved via the Hungarian method;

$\bar{m}_1$ is the maximal dimensionality of the assignment problem, i.e., the number of independent paths in the schedule execution network diagram. For example, in

Fig. 7.4, the dimensionality is equal to the job $A^{(v)}$, i.e., $\bar{n} = 6$;

σ is the duration of the planning interval;

Δt is the step length of integration for the main and the conjugate system.

Note that the integration of differential equations in the main and the conjugate system is not necessary because of their linearity. The computation can be performed subject to simple, recurrent formulas. The step for the recurrent calculations may be variable, subject to significant events which influence the current

(“active”) field of operations (gray colored operations in Fig. 7.4). These events may include, e.g., the completion of one operation, a pre-emption of an operation, or the arrival of a new operation.

Complexity of the linear programming problem can be estimated according to the complexity of the simplex method which can be used to solve the above-mentioned linear programming problem. This complexity can be estimated for one iteration as $O\left(\left(\bar{n} \cdot \bar{s} \cdot n\right)^2 + \bar{n} \cdot \bar{s} \cdot n^2\right)$, where $\bar{n}$ is the maximal number of jobs executed in parallel within the planning interval, $\bar{s}$ is the average operation number of the jobs, and n is the maximal number of machines working in parallel. Similar to (7.86), the complexity of the linear programming calculation within the MSA can be estimated as shown in Eq. (7.87):

$$O\left(\left(\bar{n} \cdot \bar{s} \cdot n\right)^2 + \bar{n} \cdot \bar{s} \cdot n^2\right) \cdot \left(\frac{\sigma}{\Delta t}\right) \quad (7.87)$$

Thus, the total complexity at one MSA iteration is as defined in Eq. (7.88):

$$\bar{N} < \left[O(\bar{m}_1) + O\left(\left(\bar{n} \cdot \bar{s} \cdot n\right)^2 + \bar{n} \cdot \bar{s} \cdot n^2\right) \right] \cdot \left(\frac{\sigma}{\Delta t}\right), \quad (7.88)$$

where $\bar{N}$ is the average number of additional operations.

Since the complexity of the integer and linear programming problems at each cut is polynomial and the number of integration steps and iterations increases linearly, the computational complexity of the scheduling algorithm is polynomial. The proof is complete.

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Chapter 8

Simulation Applications to Structural Dynamics in Service and Manufacturing Supply Chain Risk Management

8.1 Simulation Model of Service Supply Chain Design with Facility Disruption Considerations

8.1.1 *Brief Overview*

Facility disruption impact on supply chain performance is studied using the example of outsourced academic journal publishing services affected by recent floods in Chennai. A discrete event simulation model is used to identify the performance impact of facility disruptions for the primary vendor. Eighteen scenarios are analyzed in terms of different disruption durations, sourcing strategies and demand patterns. Sensitivity analysis is performed for several input parameters to illustrate the model's behavior. The analysis allows identification of the optimal sourcing strategy depending on a combination of factors: duration of disruptions, demand patterns and sourcing costs. The results indicate that higher performance can be observed by increasing the dual sourcing component as disruption durations increase. The results have some major implications. First, the analysis can be used to identify the patterns “disruption duration – sourcing strategy” with the lowest performance decrease in order to employ the most efficient reactive sourcing strategy. Second, it becomes possible to identify the most preferable (in terms of sales or efficiency) proactive and reactive sourcing strategies and compare the impacts of different patterns “demand – disruption duration – sourcing strategy” according to multiple performance dimensions.

8.1.2 *Verbal Problem Description*

Service supply chains (supply chain) and sourcing strategies for such supply chains have been a visible research avenue over the last decade (Wang et al. 2015; Choi et al. 2016). Unlike in manufacturing supply chains, the disruptive risks in service supply chains have not yet been a very well explored, whereas operational risks have attracted the attention of the research community (Sethi et al. 2007; Choi 2013; Stavroulaki and Davis 2014; Wang et al. 2015; Choi et al. 2016). In manufacturing supply chains, single vs dual sourcing decisions have been a well studied in the last two decades (Gupta et al. 2015; Nair et al. 2015). Sourcing strategy is recognized as a key driver of supply chain resilience (Snyder et al. 2016).

In recent years, supply chain severe disruption management has extended the scope of research in single vs dual sourcing analysis (Yu et al. 2009; Iakovou et al. 2010; Lu et al. 2011; Yang et al. 2012; Ho et al. 2015; Tsai 2016). Severe disruptions in supply chains are low-frequency-high-impact disruptions. Examples include fires, floods, tsunamis, political crisis, etc. Fundamental concepts comprise proactive design of sourcing strategy and reactive adaptation of sourcing strategy in the event of disruption (Ivanov et al. 2017). Capacity buffers, back-up facilities and suppliers are typically considered in light of supply chain resilience (Ambulkar et al. 2015; Ivanov et al. 2016; Sokolov et al. 2016; Ivanov 2017a). Snyder et al. (2016) point out the integration of proactive and reactive strategies as a crucial research domain.

In addition, a research gap can be identified in terms of research methodology which is predominantly based on optimization methods (Cui et al. 2010; Li et al. 2013; Sawik 2016) while simulation modelling remains underutilized (Deleris and Erhun 2011; Schmitt and Singh 2012). This holds true for both manufacturing and service supply chains. A practical overview of simulation model examples for service supply chains can be found in the study by Pezzotta et al. (2016).

Consider an example of severe disruption in service supply chains. The floods in the Indian state of Tamil Nadu in November–December 2015 significantly disrupted supplies of fuel and auto parts in India as well as the operations of a number of academic journals since this area is the world's leading location for academic journal composition services. As it was reported by Stewart Gardiner, Journals Production Director of Taylor and Francis Group, "The main commercial centre, Chennai, was declared a disaster area on 2 December... Fortunately the rains have now ceased and operations are returning to normal with full restoration of services expected by 21 December... However, the disruption will adversely affect our publishing programme, with a significantly larger number of issues expected to publish late in December 2015... Please be assured that Taylor & Francis production staff are doing everything in their power to bring publication schedules back on track and restore a high-quality, efficient and responsive production service for our editors and authors" (IADA 2016).

Motivated by this severe disruption in the service supply chain and the previously identified research gaps in regard to severe disruptions in service supply

chains and simulation modelling of such disruptions, the objective of this study is to extend the exiting body of literature on proactive and reactive sourcing strategies in the service supply chain in regard to single vs dual sourcing analysis by incorporating considerations of capacity disruptions using the simulation modelling approach.

The specifics of service supply chains, such as the absence of inventory and shipments, large processing volumes and in-place production, differentiate them from manufacturing supply chains as a specific research object in terms of risk management and ripple effect analysis and provide a challenging environment for new research.

Research gaps can be identified, therefore, on the interface of sourcing strategy-simulation and simulation model-risks in service supply chains. To the best of our knowledge, there is no published research on simulation-based single vs dual sourcing analysis in the service supply chain with consideration of capacity disruptions. We consider it a research opportunity that can enlarge the existing body of knowledge on decision-support systems for service supply chains.

8.1.3 Problem Statement and Modelling Approach

We consider a two-stage supply chain in academic journal publishing services that comprises a vendor, a back-up vendor and customers (Fig. 8.1).

Under normal conditions, a back-up vendor is not used. The problem considered consists in analysis, using simulation, of a single vs dual sourcing strategy where disruption occurs in the main vendor's capacity. A vendor, a backup vendor and a number customers (i.e., academic journals) are considered. We include the following parameters in the problem statement:

- A one-month period is considered;
- Capacity at the main vendor can be disrupted to different extents;
- A backup vendor can be used via dual sourcing;
- Period demands for the customers are known.

We are interested in qualifying the impact of capacity disruptions at the main vendor on overall supply chain performance in the service supply chain for low and high demand patterns and developing a recommendation on a single vs dual sourcing strategy. The following KPI (key performance indicators) are included in the analysis:

- Total revenue (i.e., turnover at vendors)
- Total costs (i.e., sum of production costs)
- Profit (i.e., difference between total revenue and total costs)
- Order fulfillment (i.e., number of completed customer orders).

The methodology of this study is based on discrete-event simulation using the standard multimethod simulation software anyLogistix (Ivanov 2017b). The

Fig. 8.1 Two-stage service supply chain



following model structure has been used. First, in the block “source,” demands for customers are setup based on periodic demand data. In the block “ordering,” sourcing policies (single or dual sourcing) are setup and matched logically with customers and demand forecasts. Similarly, in the block “production,” processing capacities for vendors are setup.

We consider three different durations of capacity disruption (i.e., long disruption period, medium disruption period and short disruption period), two different demand periods (i.e., high and low demand) and two different options for dual sourcing (i.e., full flexibility of the backup vendor and partial flexibility of the backup vendor). This implies 18 scenarios for consideration in the experiments.

By decreasing capacities at different points of time and for different durations, performance impacts are observed for 18 scenarios. Performance impact is considered in terms of revenue, total costs and order fulfillment rate. Finally, we perform analysis of the experimental results to develop recommendations on service supply chain protection and mitigation of performance degradation. The objective of the simulation experiments is to reveal dependencies between disruption durations and demand level in regard to selection of sourcing strategies with consideration of capacity disruption.

8.1.4 Data for Simulation

A vendor, a backup vendor and five customers (i.e., academic journals) are considered. We include the following parameters in the problem statement:

- A one-month period is considered;
- Capacity at the main vendor in Chennai can be disrupted to three extents: disruption happens on the 1st of the month, on the 9th of the month and on the 20th of the month; in other words three disruption durations are considered (30 days, 21 days and 10 days);
- A backup vendor in Pune can be used via dual sourcing subject to two options, i.e., medium flexibility (MF) and full flexibility (FF). Medium flexibility assumes that backup vendor capacity is limited to 500 units a month, while full flexibility implies that backup vendor capacity can be increased to any level to cover the disrupted capacity at the primary vendor;
- Normal production costs at the primary vendor are \$0.5 per unit;
- Costs of service usage from the backup vendor are \$0.8 per unit in case of MF and \$0.9 per unit in case of FF;
- Revenue for the customer for a completed demand unit is \$1;

Table 8.1 Daily demand patterns

Customers	Low demand	High demand
1	5	10
2	10	20
3	5	10
4	3	6
5	15	30

- Period demands for the customers are known;
- Two demand patterns are considered, i.e., low period demand (LD) and high period demand (HD) (Table 8.1).

The experimental part comprises consideration of the following disruption and reconfiguration scenarios (Table 8.2).

In varying demand patterns, sourcing strategy and disruption durations, 18 scenarios are considered in total. The comparisons and recommendations will be based on the following KPIs: total revenue, total costs, profit and order fulfillment rate.

8.1.5 Simulation Results

The simulation results for the performance impact analysis of the sourcing strategies for the 18 scenarios (cf. Table 8.2) are depicted in Figs. 8.2 and 8.3.

Figure 8.2 depicts performance impact according to disruption duration. It can be observed from Fig. 8.2 that profits decrease when disruption durations increase for all sourcing strategies. In the case of a 10-day disruption, a dual sourcing strategy with medium flexibility provides the highest profit, followed by the dual sourcing strategy with full flexibility. This holds true for both low and high demand patterns. In the case of a 21-day disruption, the same effects can be observed, whereas the difference between profits in a dual sourcing strategy with medium flexibility (\$400) and a dual sourcing strategy with full flexibility (\$228) in case of a high demand pattern is much greater than in the case of a 10-day disruption (\$800 and \$788 respectively). In the case of a 30-day disruption, the highest profit is achieved through a dual sourcing strategy with full flexibility (\$228), whereas the gap to other strategies exceeds 100%. On the customer side, clear domination of a dual sourcing strategy with full flexibility can be observed for all demand patterns and disruption duration periods except for low demand and 10-day disruption.

Insight 1. If disruption duration is short, the efficient flexibility option can be recommended independently from demand pattern. An increase in disruption duration makes the dependence between sourcing strategy and demand peaks obvious. For short and medium disruption durations, an efficient dual sourcing option should be selected if service level is not the primary company objective. Otherwise,

Table 8.2 Simulation scenarios

Scenarios	Disruption 30 days		Disruption 21 days		Disruption 10 days	
	Low demand (LD)	High demand (HD)	Low demand (LD)	High demand (HD)	Low demand (LD)	High demand (HD)
Single sourcing	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
	SS_LD_30	SS_HD_30	SS_LD_21	SS_HD_21	SS_LD_10	SS_HD_10
Dual sourcing medium flexibility (MF)	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
	MF_LD_30	MF_HD_30	MF_LD_21	MF_HD_21	MF_LD_10	MF_HD_10
Dual sourcing full flexibility (FF)	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
	FF_LD_30	FF_HD_30	FF_LD_21	FF_HD_21	FF_LD_10	FF_HD_10

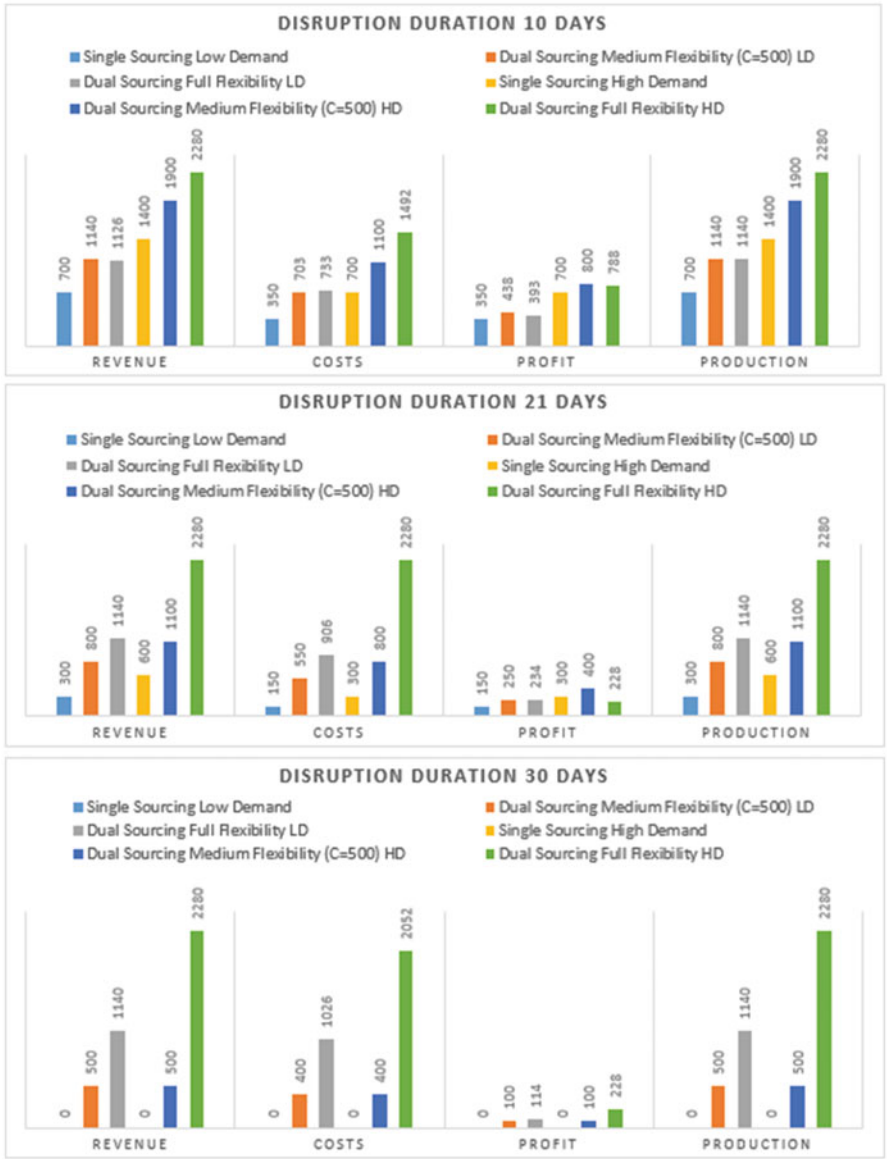


Fig. 8.2 Performance impact analysis according to disruption duration

and for long disruption durations, full dual sourcing flexibility can be recommended independently from demand pattern.

Figure 8.3 provides a detailed performance impact analysis of different disruptions and dual sourcing strategies in high demand periods separately. It can be

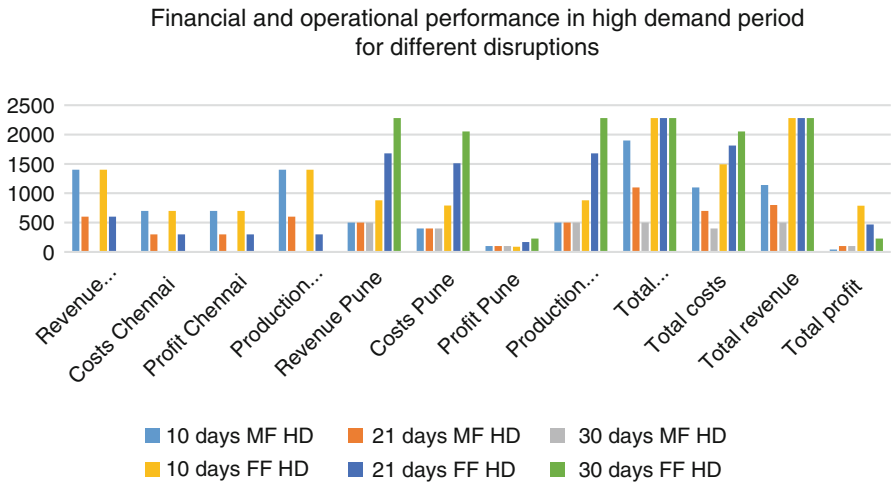


Fig. 8.3 Detailed performance impact analysis for dual sourcing strategies

observed from Fig. 8.3 that while total service production volumes and total revenue exhibit the same profiles, total profit profiles are different for medium and full dual sourcing strategies. On the one hand, we can observe that the highest profits can be achieved in the case of 10-day disruption if using dual sourcing with full flexibility. On the other hand, profits increase with increasing disruption duration when a medium flexibility, dual sourcing strategy is used.

Insight 2. Dual sourcing can be recommended for scenarios with significant discrepancies between demand, disruption durations and primary vendor capacity patterns and significant reductions in order fulfillment in the event of disruption. The simulation results also allow recommendation of full back-up flexibility use if applying dual sourcing.

8.1.6 Managerial Insights

Literature analysis and numerical experimental results point to some important managerial insights. The mutual dependencies of sourcing strategies, disruption durations and demand patterns are depicted in Fig. 8.4.

The following observation and recommendations can be summarized. First, with the help of the developed model, it becomes possible to identify the patterns of “disruption duration – sourcing strategy” with the lowest performance decrease in order to employ the most efficient reactive sourcing strategy (cf. Fig. 8.3). Second, an identification of the most preferable (in terms of order fulfillment or efficiency) proactive and reactive sourcing strategies is included in the managerial outcomes of the presented approach (cf. Fig. 8.2).

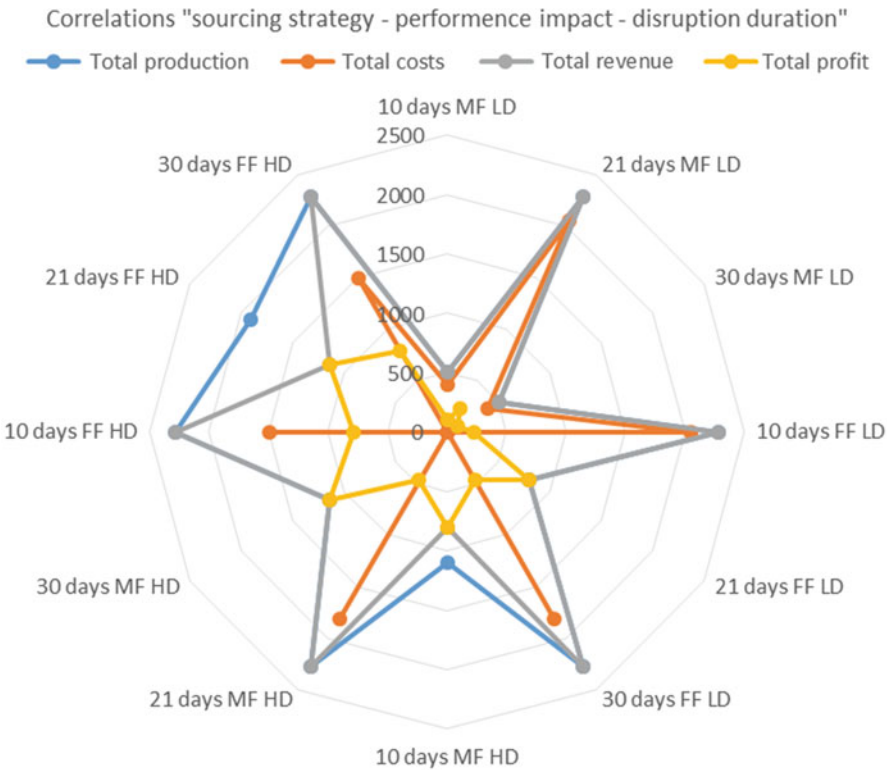


Fig. 8.4 Mutual dependencies of sourcing strategies, disruption durations and demand patterns

Third, the supply chain managers can compare the impacts of different patterns of “demand – disruption duration – sourcing strategy” according to multiple performance dimensions (financial, customer and operational performance). Fourth, managers can study order fulfillment impact analysis in regard to different customers individually in order to employ a reactive sourcing strategy that prioritizes customers according to importance. In addition, such analysis can be useful in the proactive stage when development contracts, with possible considerations for disruptions, are made with the vendors and customers. Fifth, correlations between the duration of disruptions, demand patterns and sourcing strategies can be observed from the experiments. A higher performance can be observed when the dual sourcing component is increased with an increase in disruption duration.

The experimental results point to the conclusion that dual sourcing can be recommended for the scenarios with significant discrepancies between demand, disruption durations and primary vendor capacity patterns and significant reductions in order fulfillment in the event of disruption. Given the simulation results, it is also recommended to use full back-up flexibility if applying dual sourcing.

In light of these reflections, simulation application for modelling the supply chain with consideration of disruption can be identified in the several areas. The possibility to change parameters dynamically during the experiment and the observe performance impact of these changes in real-time close some research gaps, e.g.:

- Analysis of disruption propagation in the supply chain;
- Consideration of dynamic recovery policies;
- Incorporation of gradual capacity degradation and recovery actions in the management analysis;
- Quantification and interrelation of multiple dimensions of performance impact including financial, service level and operational performance.

Such simulation analysis is of vital importance for production coordinators and dispatchers in service supply chains at tactical and operative decision-making levels, while optimization methods provide rigorous decision-making support for supply chain executives at the strategic level. Simulation-based optimization can be considered, in this regard, as a technique that can integrate decision-making at the strategic and tactical-operative levels.

The results can be used by supply chain managers to:

- identify the patterns of “disruption duration – sourcing strategy” with the lowest performance decrease in order to employ the most efficient reactive sourcing strategy;
- identify the most preferable (in terms of on-time order fulfillment or efficiency) proactive and reactive sourcing strategy;
- compare the impacts of different patterns “demand – disruption duration – sourcing strategy” on multiple performance dimensions (financial, customer and operational performance)
- observe order fulfillment impact analysis in terms of different customers individually in order to employ a reactive sourcing strategy that includes prioritization of customers by importance
- develop contracts with vendors and customers with possible disruption considerations.

Future research on simulation-based service supply chain modelling with disruption considerations is multi-faceted. It may include extensions both conceptual and technical. In the conceptual part, more detailed scenarios, sourcing strategies and KPI schemes can be explored. While this study focused on strategic issues of sourcing strategy selection, future research may be more operative and address detailed recovery policies, such as overtime work, gradual capacity recovery, etc.

8.2 Simulation Model of Supply Chain Planning with Production Capacity Disruption Considerations

8.2.1 Brief Overview

We study the impact of production capacity disruption on supply chain resilience and efficiency. Requirements on efficiency typically result in safety stock reductions and full capacity utilization. On the other hand, consideration of the production capacity disruption risks may lead to safety stock increases and implementation of redundant capacities. With the help of the developed discrete-event simulation model it becomes possible to approach these trade-offs and compare supply chain performance in regard to the singular and combinatorial impact of individual inventory and production factors on overall efficiency and effectiveness subject to near-optimal parametrical settings. Real data from an FMCG company is used to perform simulation experiments in AnyLogic and to derive novel managerial insights and practical recommendations on inventory, on-time delivery and service level control.

8.2.2 Verbal Problem Statement

The capacity disruption impact on supply chain efficiency and resilience depends on both proactive resilience measures and recovery contingency plans (Tomlin 2006). Rice and Caniato (2003), Kleindorfer and Saad (2005) and Sheffi and Rice (2005) considered sourcing flexibility, inventory and capacity excessiveness as the major resilience drivers in the supply chain. These studies also point out that in some cases planned supply chain performance cannot be fully restored.

Song and Zipkin (2009) developed inventory control policies and analyzed inventory system performance in a multi-source supply chain in the presence of lead time uncertainty from each source. Kouvelis and Li (2012) approached contingency strategies in managing supply chains with uncertain lead-times. Atan and Snyder (2012) analyzed different strategies of capacity excessiveness with inventory control considerations.

Tomlin (2006) and Kim and Tomlin (2013) dealt with capacity expansion and a restoration problem and indicated that if recovery capacity investment is the only option, the firms in a decentralized setting overinvest in capacity, resulting in higher system availability, but at a higher cost. If both investments can be made, the firms typically underinvest in failure prevention and overinvest in recovery capacity. Schmitt and Singh (2012), Simchi-Levi et al. (2015), Ivanov et al. (2016), Schmitt et al. (2017), and Dolgui et al. (2018) investigated the performance impact of disruptions in the supply chain under considerations of recovery time. Trucco et al. (2017) analysed an Italian FMCG supply chain and simulated its resilience in AnyLogic. The results suggest developing coordinated control strategies in the case of severe supply chain disruptions. These results in line with the insights provided in the study by Schmitt et al. (2017) and Ivanov and Rozhkov (2017).

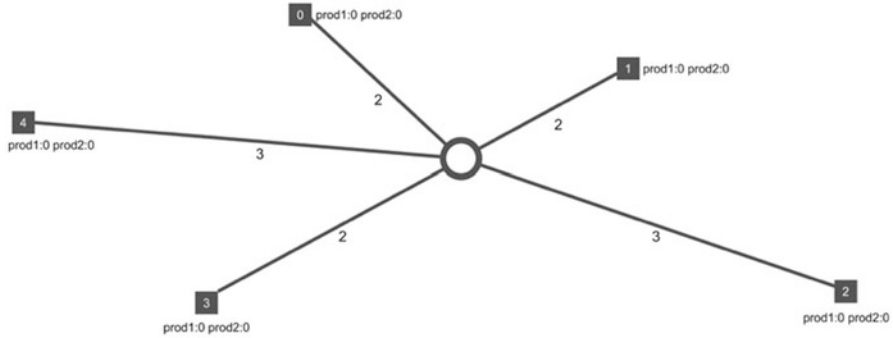


Fig. 8.5 Supply chain structure

We consider a two-product, two-stage supply chain with five distribution centers (DC) and one production plant in line with the study by Ivanov and Rozhkov (2017) (Fig. 8.5).

The model simulates a planning process in this supply chain for two products, A and B. Production capacity is subject to random disruptions. There are two groups of customers (for products A and B, respectively), which have different priorities, whereas customer for product A have higher priority. The demand variation is modelled via uniform distribution. In addition, there can be some random “trends” in the market which last for four periods and may change the demand. Base unit of time is a week: it’s assumed that planning happens every week, but some parameters are measured in days.

The objective is to minimize total system costs and keep the required service level. Supply chain resilience analysis is based on random disruptions that result in decreased production capacity.

8.2.3 Problem Statement and Modelling Approach

Consider the following parameters:

- Minimum order size and inventory level at DC
- Lot-size
- Queue size limits
- Setup time
- Production capacity
- Inventory holding costs
- Mean demand and variation
- Production order allocation interval
- Planning period
- Transportation costs
- Production costs

- Penalties for delays
- Mean and sigma of time duration and interval of capacity breakdown
- Remaining capacity percentage after the disruption

Particularities of the developed model result from a real-life example of the FMCG company that produces and distributes drinks. The following demand segmentation has been observed in this company: 80% of sales is generated by key customers for product A. The remaining 20% of sales go to small supermarkets that require the product B.

The planning is done for a 7 week horizon. Sales planning considers demand seasonal variations of 50% within the planning horizon whereas long-term demand changes with a duration of 4 weeks are possible where demand varies by 20%. Both demand variation parameters can be described by a triangular distribution.

Disruptions of 50% of production capacity are modelled as random events. The intervals between the disruptions and their durations are subject to normal distribution. By default, the following parameters are used: the mean interval is 100 periods and the mean duration of disruption is 20 periods. Standard deviations are 50 and 10 periods, respectively.

If inventory at the DC reaches the re-order point, a new production order is allocated, the size of which is a multiple of the minimum lot-size. The allocated order cannot be cancelled. Production planning considers lead time from the factory to the DC. If the computed production period of a batch (for both types of products) is reached, the orders enter the system and are allocated in the queues. If an order is waiting in the queue longer than the planning horizon at the DC allots, this order exits the system. If the constraint on the waiting time is met, the order is transferred into the production module. Processing start is the computed production week. Early production (i.e., schedule smoothing) is not allowed.

Setups in production costs time and money. At the same time, seldom setups may result into delivery delays and an increase in lead time variability. Setups are controlled in the model in two modes. In the planned mode without any capacity disruptions, lot-size based planning is used. For example, if five orders of the same product type are waiting in the queue, each of which is 10,000 product units, and minimum lot-size is fixed at 40,000 units, four of these five waiting orders will be batched and produced as a lot. Then the planned setup will be executed.

In the case of capacity shortage (i.e., due to a demand peak or a disruption), more flexible setup rules are implemented. Two additional parameters are monitored, i.e., the queue size of another product and the difference between the queues for the first and second products. In the case of limit excess for one of these parameters, the setup may be executed beforehand without waiting for lot production completion.

Supply chain performance is by total costs and service level. The total costs metric includes inventory holding costs at DCs, transportation costs, production costs and penalties. Holding costs are computed subject to interest rate. Transportation costs depend on the distance, order quantity, and shipment tariff. Production costs include fixed equipment-related costs (proportional to the capacity units) and setup costs. Penalties are incurred if the order size from the key customer exceeds

Table 8.3 Input data

Parameters	Parameter value
Minimum days of supply	14
Minimum order size in product units	10,000
Rolling planning horizon, in periods	7
Minimum period between production order allocations, in periods	1
Production capacity, product units per period	40,000
Lot-size	50,000

Table 8.4 Uncertainty data

Parameters	Parameter value
Mean of the interval between capacity disruptions, in periods	100
Standard deviation of the interval between capacity disruptions, in periods	50
Mean of disruption duration, in periods	20
Standard deviation of disruption duration, in periods	10
Demand variability, 1 period	50%
Demand variability, 4 periods	20%

the available delivery quantity. Service level is computed as a ratio of delivered and ordered products. Backordering is not considered.

Simulation length: 1200 weeks, warmup period: 50 weeks. The supply chain is adjustable (i.e., the location coordinates of the supply chain facilities can be changed) and production disruptions can be scheduled randomly.

AnyLogic multimethod simulation software has been used to develop the model and perform experiments.

8.2.4 Data for Experiments

Basic parameters such as demand, order size and safety stock were setup equally at DCs (Table 8.3).

Two major uncertainties in the system come from demand variability and production capacity disruptions. Therefore, the stochastic nature of these parameters influences the supply chain both from the side of the customer and the side of the supplier. Consider the preliminary analytical estimation of the uncertainty impact on system performance. Input data is shown in Table 8.4.

In the event of disruption, production capacity is decreased by 50%. According to the data from Table 8.4, the supply chain functions in disrupted mode an average of 16.6% of time. This results in a productivity decrease of about 8% as compared to the disruption-free scenario.

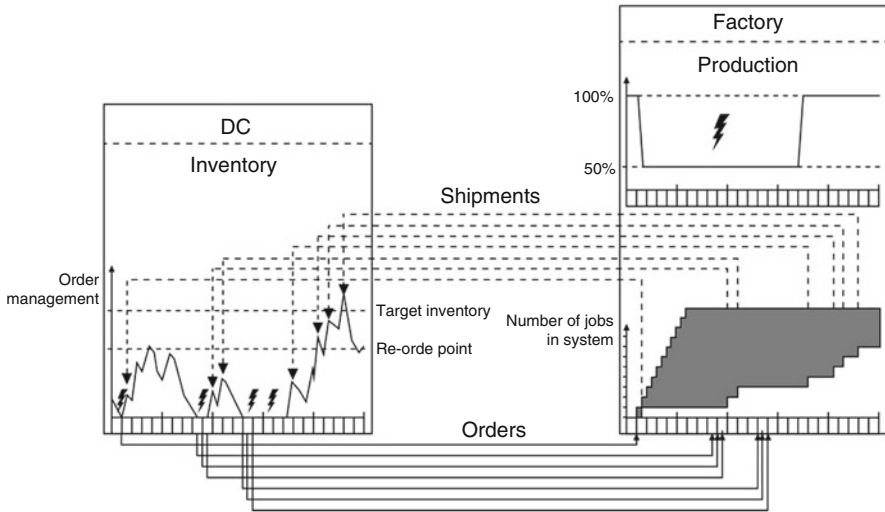


Fig. 8.6 Supply chain behavior in disrupted mode

8.2.5 Experimental Results

8.2.5.1 Disruption and Recovery Impacts on Inventory Level

Let us analyze the system's behavior in the disrupted mode subject to the data in Table 8.4. Ahead of the first disruption, the system exhibits the same behavior and performance in both normal and disruption scenarios. A disruption results in differences in system execution. After the disruption, the inventory was available for 7 periods. Two small deliveries from the factory to the distribution center can be observed within first 2 weeks following the disruption since 50% of capacity still operates. After capacity recovery, a number of delayed production orders is shipped to the distribution center implying higher inventory costs. This effect is called "*postponed redundancy*" (Fig. 8.6).

Having reached the inventory peak, the order allocation intensity changes again. The high inventory level increases the write-off risks and the system tries to allocate less production orders. In the case of delivery delays, penalties may be incurred. For example, in period #165, the inventory reaches zero, which implies lost sales. Therefore, it can be observed that *a production capacity disruption causes both product shortage and write-off risks*.

In the disruption mode, the referenced process model for the planning algorithm becomes less precise and causes *redundant order allocations* as a "*panic*" reaction. Significantly, a long planning horizon means that the system cannot react flexibly to changes. Therefore, *supply chains with a long cycle between order allocation and delivery are more sensitive to the negative impacts of production capacity disruptions*. Another conclusion from this experiment is that additional *control algorithms*

are needed to monitor system behavior, identify disruptions and adjust order allocation rules.

The only positive aspect of an excessive inventory is that the system is protected in the event of multiple recurring disruptions in a short period of time. In the case of non-perishable products, this effect would be stronger and longer.

8.2.5.2 Disruption and Recovery Impacts on On-Time Delivery Performance

Let us analyze on-time delivery performance of the supply chain subject to lost orders, delayed orders and average inventory in the supply chain in regard to both disruption and recovery periods. Lost orders start significantly increasing in some periods after a production capacity disruption, and stabilize shortly after the capacity recovery. Delayed orders start increasing almost immediately after a production disruption. The stabilization period is longer than for lost orders and its beginning is close in time to reaching maximum inventory level in the supply chain.

During the disruption, average inventory in the supply chain does not reach zero since the factory is still operating at 50% of production capacity. After capacity recovery, an inventory peak can be observed. Therefore, we conclude that the average inventory in the supply chain cannot be considered a sound indicator for analysis of a disrupted supply chain's behavior. However, *after returning to normal conditions, average inventory along with lost orders dynamics can be used as indicators of the supply chain's recovery after a disruption.* Delayed orders are one of the system's inertia indicators. *If delayed orders are increasing under conditions of stabilized service level, this indicates a significant inventory increase in the supply chain in the near future.*

Considering possible measures to mitigate inventory increase during supply chain recovery, we suggest cancelling all waiting production orders during capacity recovery. The orders waiting in the queue during the recovery period are, in essence, the orders with at least one period delay. Allocated orders should not be cancelled. It can be observed that *waiting order cancellation during the capacity recovery period prevents overstocking and write-off risks.* The inventory level does not exceed levels in the disruption-free mode. The planning algorithm can operate with actual data on delivery dates. It should be noted that if backordering were considered in the system, this measure would be less efficient. Analysis of backordering issues in the context presented can be an interesting topic for future research.

8.2.5.3 Redundancy Impacts on Costs and Service Level

In the developed model, two redundancy policies are considered:

- Inventory level increase at distribution centers
- Production capacity increase

Table 8.5 Optimal parameter values

Parameters	Scenario #1	Scenario #2	Scenario #3
Order quantity, units	10,000	10,000	10,000
Production order allocation interval, weeks	1	1	1
Days of supply for lead time 2 weeks	11	13	17
Days of supply for lead time 3 weeks	11	15	19
Capacity, units per period	40,000	50,000	45,000
Total costs, conditional monetary units	459,134	511,684	507,111

In the course of optimization experiments using OptQuest, the distribution centers are grouped according to distance to the factory, i.e., 2 or 3 weeks of lead time. Re-order point is computed individually for these two groups in order to reduce computational complexity. The optimization results for three scenarios are shown in Table 8.5.

Redundant inventory in scenario #2 leads to disruption impact mitigation through excessive production capacity, while inventory levels and distribution centers change only to a small extent. In scenario #3, long-term supply chain resilience is ensured by both inventory and capacity redundancy, but, of the two, inventory redundancy contributes more to resiliency.

It is notable to point out the important role that analysis plays in redundancy policy alignment with the planning algorithm. It can be observed from the previous analysis that inventory overage or shortage does not change the system’s behavior significantly. In the case of capacity disruption, the system behavior changes. The reasons for this can be seen in uncertain setup times, increases in waiting order queues, and delivery delays or losses.

8.2.6 Testing and Verification

For *sensitivity analysis* of the system, optimization experiments have been performed, the results of which have been used for testing system behavior in a number of scenarios. For some cases, the embedded AnyLogic optimizer OptQuest has been used to find the optimal parameter values. Cost minimization has been selected as the objective function. Service level has been considered in the constraints using 97% as the minimum acceptable value for any location of the distribution network facilities.

For *verification*, the following methods have been used: simulation run monitoring, output data analysis in the log files and testing with the help of deterministic data. For *testing*, replications with durations of 12,000 periods (weeks) with a warm up time of 50 periods have been applied.

8.2.7 *Managerial Insights*

Several specific issues can be observed in regard to supply chain resilience and the consideration of efficiency. First, the effect of “postponed redundancy” should be addressed. After capacity recovery, delayed production orders are shipped to the distribution center, which implies higher inventory costs. After this, the order allocation intensity changes again. High inventory levels increase holding costs and the system tries to allocate less production orders. In the case of delivery delays, penalties may be incurred. Therefore, a production capacity disruption causes both product shortage and high inventory costs.

Second, cancelling waiting orders for the recovery period reduces inventory holding costs while maintaining the same service level. In disruption mode, the referenced process model for the planning algorithm becomes less precise and causes redundant order allocations as a “panic” reaction: the supply chains with long cycles between order allocation and delivery are more sensitive to the negative impacts of production capacity disruptions. Additional control algorithms are needed to monitor system behavior, identify disruptions and adjust order allocation rules.

Third, it has been observed that average inventory in the supply chain cannot be considered a sound indicator for the analysis of a disrupted supply chain’s behavior. However, after returning to normal conditions, average inventory along with the lost orders dynamics can be used as indicators of the supply chain’s recovery after a disruption. Delayed orders metric indicates the degree of system inertia. If delayed orders increase under conditions of stabilized service level, this indicates a significant inventory increase in the supply chain in the near future.

Fourth, flexibility issues have been analyzed. It has been observed that the higher frequency of new production order allocations and the lower the order quantity, the more flexible is the supply chain. In comparing disruption-free and disruption scenarios without production constraints on capacity and setups, the experimental data shows that the gap between service levels in disruption scenarios and disruption-free scenarios increases as inventory levels decrease.

The results provide practical evidence, but need to be further studied and developed regarding the following issues. First, we observed that main events in the model such as disruption start, full recovery, high inventory increase, system stabilization, product write-off and the following problems with the service level are significantly distributed in time. In the simulation model, the impacts of these events on supply chain efficiency and service level can be estimated according to the final experiment results. In real life, such a retrospective analysis can only be applied conditionally to performance impact analysis.

Second, the analysis of system performance in the disruption and recovery period does not fully account for system productivity in regard to future events such as expiration dates. Expiration dates and disruptions can be therefore considered factors that depict the importance of supply chain dynamics and analysis over time.

The results also provide evidence that further research is needed in the future in regard to multi-product systems with multi-echelon supply chains. More sophisticated planning algorithms would also benefit this research field. Finally, the impacts of alignment and the synchronization of production and distribution processes on supply chain costs minimization, service level increase, and service level variation decrease with consideration of both supply chain efficiency and resilience are promising future research avenues.

8.3 Single Versus Dual Sourcing Analysis with Disruption Considerations

8.3.1 Brief Overview

Sourcing strategy analysis in the context of supply chain flexibility and in regard to single vs dual sourcing has been a well explored in research in the last two decades. In recent years, single vs dual sourcing analysis has been increasingly applied in supply chain disruption management. A supply chain simulation model with consideration of capacity disruption along with experimental results are presented in this section. A set of sensitivity experiments illustrates the model's behavior. Given the analysis, it is recommended to use single sourcing, capacity flexibility and dual sourcing for different combinations of demand and inventory patterns.

8.3.2 Problem Statement

We consider a three-stage supply chain that is comprised of a supplier, a distribution center (DC1), a back-up distribution center (DC2), and a customer (Fig. 8.7).

Under normal conditions, the back-up DC is not used. The problem consists in the analysis of single vs dual sourcing strategies and selection of one with disruption considerations for DC1 capacity using different inventory and demand patterns. We include the following parameters in the problem statement:

- A one-month period is considered;
- Capacity at DC1 can be disrupted;
- DC2 is a back-up DC;

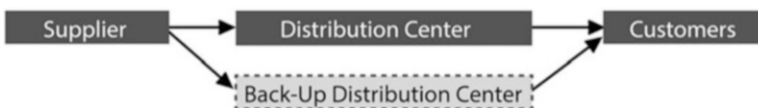


Fig. 8.7 Three-stage supply chain (Ivanov 2017c)

- At the beginning of the period, DC1's has some starting inventory subject to an inventory pattern;
- Period demand for the customer can be described by different patterns;
- Shipment time is computed automatically subject to real routes and fixed average truck speed;
- Transportation costs are subject to weight and distance;
- Inbound and outbound processing costs are known;
- Fixed facility operating costs are known;
- Inventory holding costs are known;
- Unit price is known.

We are interested in quantifying the impact of capacity disruptions at DC1 for different inventory and demand patterns and subject to overall financial, customer and operational performance in the supply chain. The following key performance indicators are included in the analysis:

Financial supply chain performance:

- Total revenue (i.e., turnover at DCs)
- Total costs (i.e., sum of production, transportation and inventory costs)
- Profit (i.e., difference between total revenue and total costs)

Customer performance:

- beta-service level (i.e., the percentage of total sales in regard to maximum customer demand during the lead-time)
- Total sales (i.e., delivered products to customers)

Operational performance:

- Inventory holding costs

8.3.3 Modelling Approach

A large-scale, discrete-event simulation model has been developed using the software anyLogistix. The developed simulation model and experimental environment exhibit the following characteristics:

- Discrete-event simulation model;
- Each structural model object in anyLogistix is an agent in the AnyLogic multimethod simulation software;
- Standard anyLogistix functionality has been used;
- Experiments have been performed using a standard notebook with 2.40 GHz CPU and 8.00 GB RAM.

In the block "demand," customers are created and demand forecasts are setup based on either historical data or periodic demand. In the block "ordering," sourcing policies from DCs to customers (e.g., single or multiple sourcing) and inventory

control policies (e.g., s, S or r, q) at DCs are setup and matched logically with demand forecasts and production. Similar, in the block “production,” sourcing policies from factories to DCs and inventory policies at factories are setup and matched logically with production policy with the possibility of using a bill-of-material. In the block “transportation,” vehicle types and path data are setup. Path data define parameters for shipments in the supply chain.

Structural dynamics in the supply chain is modelled using events of which appearance and duration may be random, scheduled or triggered by other events. Operational parameter dynamics is the key advantage of using simulation for ripple effect analysis since real complexities can be considered and analyzed. A key performance indicator dashboard can be customized on the basis of more than 200 key performance indicators that cover a large range of monetary (e.g. revenue and costs), time (e.g. lead time), quantity-based (e.g. delayed orders) or ratio (e.g. service level or on-time delivery) key performance indicators.

8.3.4 Experiments

8.3.4.1 Single Sourcing Experiment

For single-sourcing experiments, the following data was used:

- A one-month period is considered;
- Inbound capacity at DC1 is disrupted and no shipments can be received from the supplier within the one-month period;
- Outbound capacity is not disrupted;
- DC2 is not used;
- At the beginning of the period, DC1’s inventory on-hand is 20, 40 or 60 units;
- Period demand for the customer can be low (7 units per 10 days), medium (20 units per 10 days) or high (33 units per 10 days);
- Shipment time is computed automatically subject to real routes and fixed average truck speed of 80 km/h;
- Transportation costs is computed as $0.01 \times \text{weight} \times \text{distance}$;
- Inbound and outbound processing costs at DCs is each \$2 for a product unit;
- Fixed facility costs are \$5 per day;
- Inventory holding costs are \$0.1 per day;
- Price is \$100 per unit.

The experimental part considers the following disruption and reconfiguration scenarios (Table 8.6).

The simulation results for the performance impact analysis of the inbound capacity disruption at DC1 in the single sourcing case for nine scenarios (cf. Table 8.1) are depicted in Figs. 8.8 and 8.9.

It can be observed from Fig. 8.8 that the highest profit can be achieved using medium inventory quantity in the periods with medium and high demand and using

Table 8.6 Simulation scenarios

Scenarios	Monthly demand 1 (low)	Monthly demand 2 (medium)	Monthly demand 3 (high)
Low beginning inventory (20 units)	Scenario 1_20	Scenario 2_20	Scenario 3_20
Medium beginning inventory (40 units)	Scenario 1_40	Scenario 2_40	Scenario 3_40
High beginning inventory (60 units)	Scenario 1_60	Scenario 2_60	Scenario 3_60

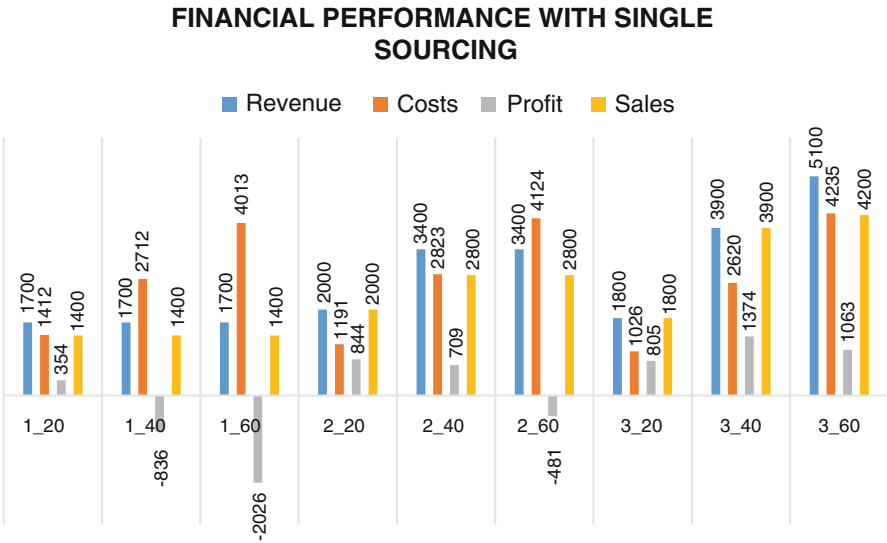


Fig. 8.8 Financial performance impact analysis of inbound capacity disruption at DC1 in the single sourcing case for nine scenarios

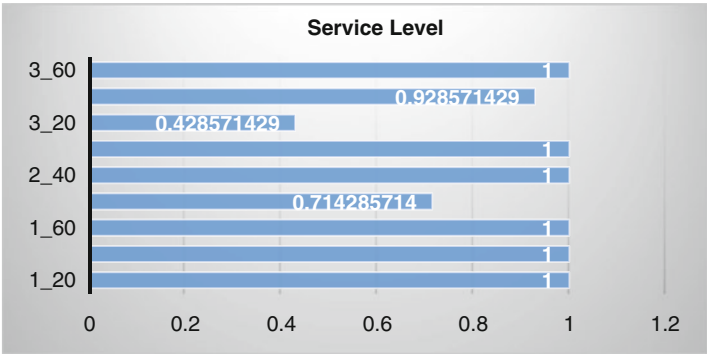


Fig. 8.9 Service level impact analysis of inbound capacity disruption at DC1 in the single sourcing case for nine scenarios

low inventory policy in the period with low demand. Losses can be observed in three scenarios (1_60, 2_40 and 2_60). From the sales point of view, it can be observed that medium and high inventory policies facilitate higher sales compared to low inventory policy in the periods with high and medium demand, while low inventory policy is the preferred solution for a low demand period.

In Fig. 8.9, service level impact analysis of inbound capacity disruption at DC1 is shown in the single sourcing case for nine scenarios. It can be observed that the service level decreases to the greatest extents in the medium and high demand scenarios if applying low and medium inventory policy, respectively.

Given the simulation results (Figs. 8.8 and 8.9), it is recommended to use low inventory policy in low demand periods and high inventory policy in medium and high demand periods if considering possible inbound capacity disruption at DC1. For scenarios 2_20, 3_20 and 3_40, dual sourcing may be recommended in the event of a service level decrease.

8.3.4.2 Dual Sourcing Experiment

For dual-sourcing experiments, the following data was used:

- A one-month period is considered;
- Inbound capacity at DC1 is disrupted and no shipments can be received from the supplier within the one-month period;
- Outbound capacity is not disrupted;
- DC2 is used for scenarios 2_20, 3_20 and 3_40;
- DC2's beginning inventory on-hand is 20, 40 or 60 units;
- Costs and lead times at DC2 are higher as at DC1.

The simulation results for performance impact analysis of inbound capacity disruption at DC1 in the dual sourcing case are depicted in Figs. 8.10, 8.11, and 8.12.

It can be observed from Fig. 8.10 that dual sourcing facilitates higher profits for scenarios 2_20 and 3_20, i.e., for the cases with low inventory policy and high/medium demand, whereas in 3_40 scenario, profit decreases as a result of dual sourcing. This can be explained by the fact that the service levels in scenarios 2_40 and 3_20 were 71% and 43%, respectively, whereas service level in scenario 3_40 was 92% (Fig. 8.11). Figure 8.12 depicts inventory dynamics in single and dual sourcing cases. Given the computational results from Figs. 8.10, 8.11, and 8.12, dual sourcing can be recommended for scenarios with significant reductions in service level in the event of disruption.

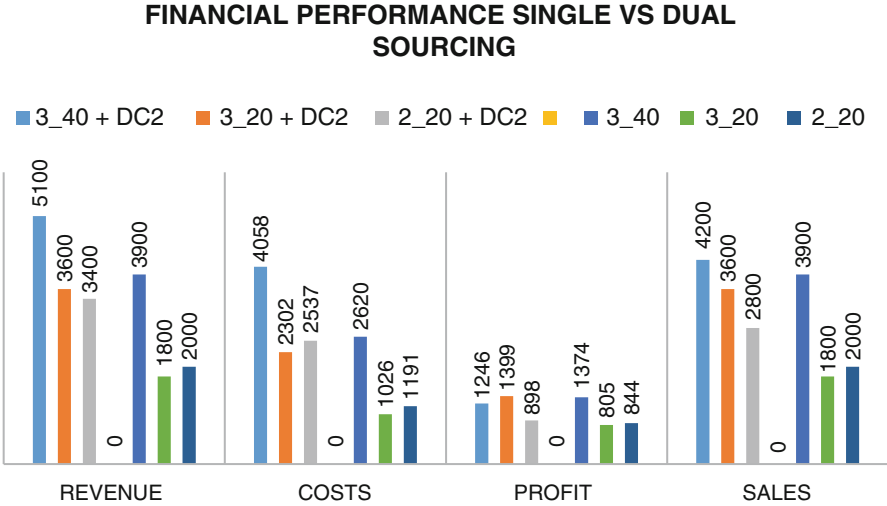


Fig. 8.10 Financial performance impact analysis of inbound capacity disruption at DC1 in the dual sourcing case

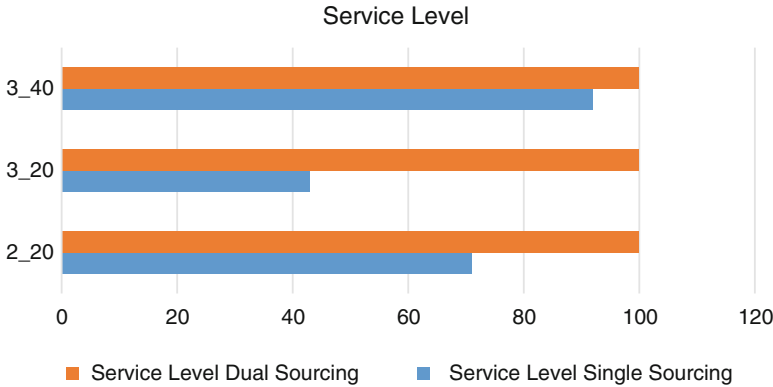


Fig. 8.11 Service level impact analysis of the inbound capacity disruption at DC1 in the dual sourcing case

8.4 Managerial Insights

It can be observed from Sect. 8.3 that both inventory quantity and demand parameters influence the performance and the decision about single vs dual sourcing. Therefore, for different constellations of demand and inventory patterns, recommendation on single vs dual sourcing can be obtained according to the following matrix (Fig. 8.13).

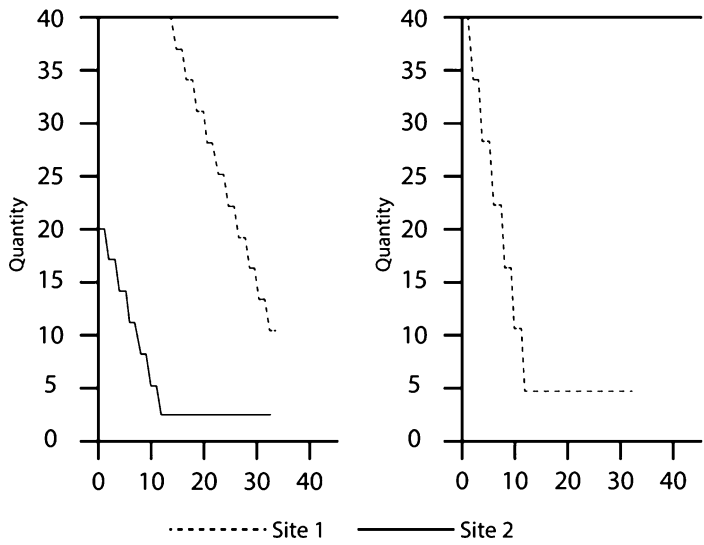
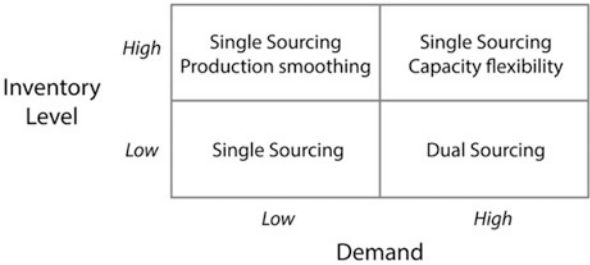


Fig. 8.12 Inventory dynamics in single and dual sourcing cases

Fig. 8.13 Sourcing strategies with supply chain disruption considerations (Ivanov 2017c)



It can be observed from Figs. 8.9, 8.10, 8.11, and 8.12 that the highest profit can be achieved using medium inventory quantity in the periods with medium and high demand and using low inventory quantity in the period with low demand. Losses can be observed in the scenarios where demand patterns have significant discrepancies with inventory patterns (e.g., scenarios 1_60, 2_40 and 2_60). Similarly, from the sales point of view, it can be observed that medium and high inventory policies facilitate higher sales as compared with low inventory policy in the periods with high and medium demand, while low inventory policy is the preferred solution for a low demand period.

As pointed out before, Fig. 8.10 shows that dual sourcing generates higher profits for scenarios 2_20 and 3_20, i.e., for the cases with low inventory policy and high/medium demand, whereas in 3_40 scenario profit decreases from use of dual sourcing. Scenarios 3_40 and 3_60 make it evident that in the cases of high demand pattern and medium/high inventory pattern, it is recommended to maintain some

level of capacity flexibility in DCs and in contracts of DCs with factories rather than invest in dual sourcing.

The computational results show that dual sourcing can be recommended for scenarios with significant discrepancies between demand and inventory patterns and significant reductions in service level (about 30–60%) in the event of disruption. Given the simulation results it is also recommended to use low inventory policy in low demand periods and high inventory policy in medium and high demand periods if considering possible inbound capacity disruption at DC1. For scenarios 2_20, 3_20 and 3_40, dual sourcing is recommended if there is a significant service level decrease after disruption.

In light of the considered reflections and literature analysis, some directions for simulation application to modelling the supply chain with disruption considerations can be derived. The possibility to change parameters dynamically during the experiment and observe the performance impact of these changes in real-time closes several research gaps, e.g.:

- Consideration of dynamic recovery policies
- Consideration of gradual capacity degradation and recovery
- Consideration of multiple performance impact dimensions including financial, service level and operational performance

Such simulation analysis is of vital importance for supply chain operations planners and dispatchers at tactical and operative decision-making levels, while optimization methods provide rigorous decision-making support for supply chain executives at the strategic level. By making changes to the simulated supply chain, one expects to gain understanding of the dynamics of the physical supply chain. Simulation is an ideal tool for further analyzing the performance of a proposed supply chain design derived from an optimization model. Simulation-based optimization can be considered in this regard as a technique that can integrate decision-making at both strategic and tactical-operative levels.

8.5 Simulation Application to Supply Chain Structural Dynamics Analysis

In this section, we derive a framework for application of simulation research methodology in supply chain structural dynamics analysis on the basis of the study by Ivanov et al. (2017).

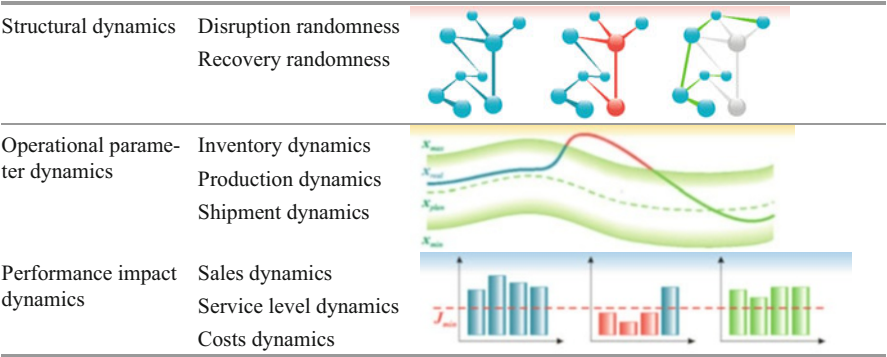


Fig. 8.14 Framework for investigating structural dynamics in the supply chain with the help of simulation research methodology (Ivanov 2017b)

8.5.1 Simulation Framework

In Fig. 8.14, a general framework for investigating the ripple effect in the supply chain with the help of simulation research methodology is presented.

Let us consider in detail the content of the different levels in the framework for investigating the ripple effect on supply chains with the help of simulation research methodology.

8.5.1.1 Structural Dynamics Level

Randomness in Disruptions

The first stage is to decide how to model the disruptions. Realistic estimations are important here in regard to frequency and duration of disruptions. One possible option is to work with homogenous or heterogeneous probabilities of disruptions in different supply chains elements. The second option is to perform a preliminary analysis and to derive the most critical elements in the supply chain in regard to the ripple effect’s impact on the supply chain’s performance. For these critical elements, random or scheduled disruption events can be modelled with a probability distribution in regard to their duration.

Randomness in Recovery

The ripple effect’s impact on the supply chain’s performance depends both on the severity of disruptions and the speed and scale of recovery actions. Recovery can be modelled in two basic ways. The simplest way is to schedule different periods of capacity restorations and assign some recovery costs in the case of which the

quickest recovery may imply the highest recovery cost. The second way is to program individual recovery policies and to define the rules of recovery policy activation dependent on the occurrence time, expected duration and the severity of the disruption in regard to both local disturbances and the ripple effect's propagation and impact on the supply chain's performance.

8.5.1.2 Operational Parameter Dynamics Level

Inventory, supply, production and transportation dynamics belong to major supply chains' processes which are influenced by disruptions and recoveries and which, in turn, influence supply chains' behaviour and the severity of the ripple effect. At this stage, inventory control policies, back-ordering rules, production batching and scheduling algorithms, as well as shipment rules and policies, need to be defined and balanced with each other for both normal and disrupted modes. Some preliminary analysis may be helpful in this area in regard to safety stocks, reorder points, etc.

8.5.1.3 Performance Impact Dynamics Level

The direct impact of the ripple effect is reflected in the changes of key performance indicators. Revenue, sales, service level, fill rate and costs are typically considered in this setting. A number of issues need to be addressed in this area. The first is to decide whether planned performance needs to be fully recovered or if changes to key performance indicator targets are acceptable. Next is to decide whether the planned key performance indicator targets need to be recovered as soon as possible or whether at the end of the planning horizon. The final step is to decide how to aggregate the individual performance impacts of the ripple effect at different nodes and arcs in the network.

8.5.2 *Application of Simulation Modelling to Supply Chain Structural Dynamics*

It can be observed from the literature review and experiments that optimization and simulation studies on supply chains dynamics and disruptions differ from each other regarding problem statements, complexities and analysis objectives (Fig. 8.15).

Optimization studies empower decision makers to determine performance impact and resilient supply chain redesign policies within rigorous analytical solutions. These studies consider a large variety of parameters, variables and

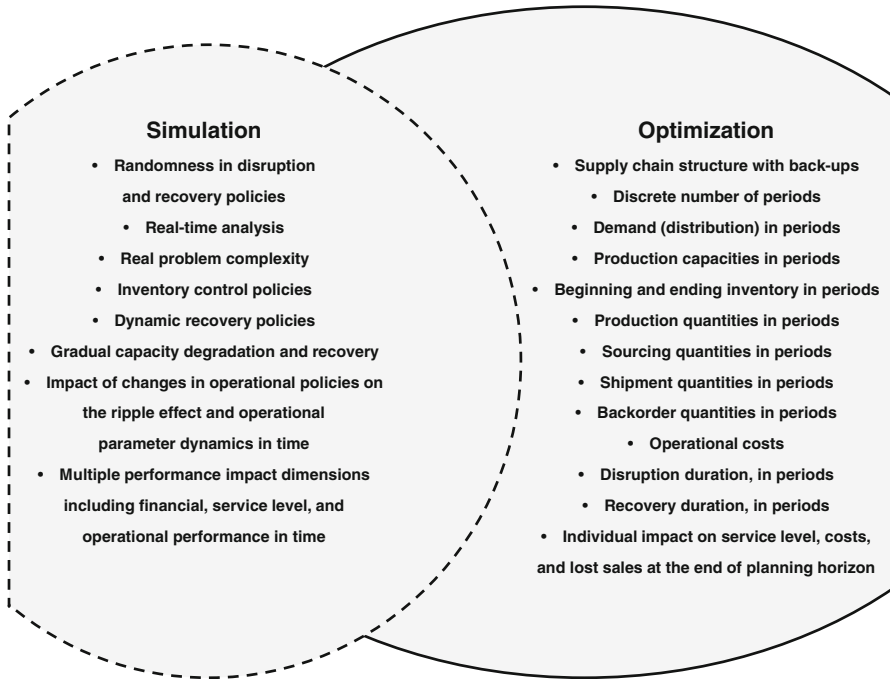


Fig. 8.15 Optimization and simulation models for supply chain structural dynamics analysis

objectives. However, in many cases simulation can enlarge the scope of a ripple effect investigation.

In optimization studies, performance impact analysis has been typically performed in regard to disrupted elements, assuming that other elements are not affected by that disruption and continue operation in the planned mode (apart from a few studies, e.g., Losada et al. 2012; Liberatore et al. 2012; Lee et al. 2014; Ivanov et al. 2016).

Optimization studies typically reduce real complexity in order to obtain feasible solutions in a reasonable time. By nature, randomness and time-related aspects of disruptions and recovery actions are difficult to represent within closed forms of mathematical equations.

State-of-the-art simulation research shows correlations between proactive strategies (backup vendors, inventory levels and control policies, and capacity buffers and flexibility), performance impact, disruption duration, disruption location, disruption propagation and recovery dynamics.

First, simulation literature provides evidence that disruption duration and propagation impact supply chain performance. Second, proactive strategies such as backup facilities and inventory have positive impacts in regard to both performance and prevention of disruption propagation. Third, speed of recovery plays an

important role in mitigating the performance impact of disruptions. Fourth, an increase in supply chain resilience incurs significant costs in the supply chain.

However, even in simulation studies, disruption duration has been typically modelled without explicit integration with dynamic recovery time and costs. The performance analysis of the use of supplier failure probabilities dominates the research domain. At the same time, another important question of disruption propagation and supply chain design survivability, with regard to both service level and costs, is still at the early stages of investigation. The role of recovery policies needs to be analyzed in more detail.

The expected managerial results of ripple effect analysis in the supply chain are to provide new insights in regard to the following questions:

- When does one failure trigger an adjacent set of failures?
- Which supply chains structures are particularly sensitive to the ripple/domino effect?
- What are the typical ripple effect scenarios and what is the most efficient way to react in each of these scenarios?

In light of the reflections considered, some directions for simulation application to ripple effect modelling in the supply chain can be derived. As observed, being able to change parameters dynamically during the experiment and to observe the effect of these changes addresses the following research gaps: disruption propagation in supply chains, dynamic recovery policies, gradual capacity degradation and recovery and multiple performance impact dimensions. Simulation analysis is key tool for supply chains operations planners and dispatchers as it informs decision-making at the tactical and operative levels, while optimization informs decision-making at the strategic level.

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Chapter 9

Entropy-Based Supply Chain Structural Complexity Analysis

9.1 Supply Chain Structural Dynamics and Complexity

9.1.1 Supply Chains as Complex Systems

Although supply chains are often referred to as complex systems, a discussion on why they are is rarely given. The problem of complexity has various aspects and applications (Simon 1962; Bertalanffy 1968; Mesarovic and Takahara 1975; Casti 1979). The literature on complexity shows that the viewpoints regarding the concept of “complexity” tend to be as richly varied as complexity itself. Although no unified definition of a complex system exists, a number of views on complexity may be distinguished.

The first group of complexity factors is related to *structural* complexity. This consists of several elements in a system and the interrelations between these elements. Moreover, the variety of the elements and interrelations is under consideration.

The second group of complexity factors is related to *functional* complexity. This includes the dynamics of the change in elements, their variety and interrelations between the elements. Another aspect is the consideration of system complexity at certain instants of time. A system can be composed of a great number and variety of elements and interrelations, but, in a snap-shot at an instant of time, the system may appear to be very simple. Finally, in functional complexity is the uncertainty of the change in the elements, their variety and interrelations between the elements. This point is one of the most critical when considering system complexity.

The third group of complexity factors is related to *modelling* complexity. To this group belongs the well-known calculation complexity, resulting, e.g. in NP (nondeterministic polynomial)-hard problems and decision-making complexity, resulting from conflicting goals that are in turn difficult to formalize (Casti 1979). The problems in systems are tightly interrelated. However, different methods and

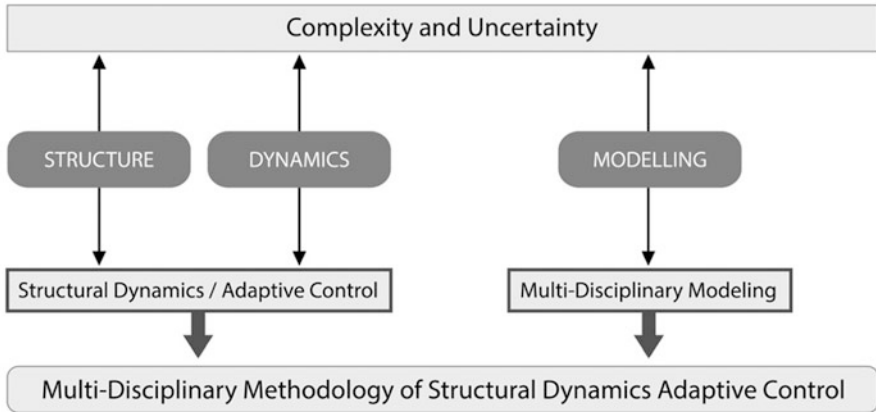


Fig. 9.1 Supply chain complexity and necessary research approaches

data are needed for solving different tasks. Usually, investigations into a complex system are performed by means of the combined application of different methods and involve specialists in economy, mathematics and computer science.

Figure 9.1 depicts the above-described complexity and uncertainty factors and proposes approaches to handle these factors.

Supply chains are characterized by a great number and variety of elements and their interrelations. Moreover, decisions in supply chains are dispersed over different structures and management levels (Ivanov et al. 2017). The supply chain structures change in dynamics, so structure dynamics is frequently encountered. Supply chain dynamics is characterized by uncertainty. Besides, supply chains are described by means of different modelling approaches and model classes. Moreover, elements of supply chains are active. They are self-goal-oriented and autonomous, but collaborative and contain conflicting goals. These goals are also subject to multiple criteria and are difficult to formalize. Here, the tight interlink between complexity and uncertainty can be perceived.

Since supply chains continuously interact with the environment and evolve through these interactions, they may be also considered open systems. To remain manageable, supply chains should maintain certain steady states for a specific period of time. These steady states result from the continuous balancing of inflow and outflow from and to the supply chain environment. This balancing is based on managerial control inputs of both a planned and a regulative nature regarding perturbation influences from the environment. We understand the environment as being everything that is not in our system (supply chain). This connection “system–environment” is subject to changes by narrowing and broadening the system’s borders. In actual open systems, these narrowing and broadening processes are based on self-organizing and self-learning principles. Modern supply chains are still far from this stage but they are following the path to self-organization.

Hence, supply chains may be justifiably called *complex dynamic multi-structural systems with active elements of free-will behaviour*. Research on such systems requires the application of different methods and disciplines. Research on supply chains as complex systems should impart much more universality than is really considered in today's social and business systems.

The process of order realization in supply chains is functionally and structurally complex and multi-staged. Additional factors of complexity are the external uncertainty, where supply chain processes are realized, and internal uncertainty and ambiguity, which is the part of the complex system that has active elements. The operational and economic results of separate operations' deviation from the plan can be a kind of internal uncertainty form that can demand a revision of the planned process course. Thus, even at the planning stage, the process should be considered ambiguous and "branchy" as a result of decision making under the current circumstances. However, the ambiguity of a process course, or its trajectory, can also be caused by other factors (in particular, by multi-variant ways of realizing process steps (functions)).

Hence, the desired result can be reached by various methods that have unequal parameters and open unequal possibilities for the performance of the supply chain's subsequent stages. A supply chain stage (or echelon) we understand in this case as the basic unit into which the supply chain can be functionally divided: for example, sourcing, manufacturing and distribution. Such ambiguity and a multi-variant approach are considered positive, as the wider the possibilities for selection the further development of a supply chain within a certain direction are, and the better they can be adapted to current conditions, which were uncertain at the planning stage.

This structure can be described with various degrees of detailed elaboration and, accordingly, can be characterized by various (structural) complexities or a variety. The assessment of this structure characteristic can be intuitively related to the quantity of business process courses, the quantity of polytypic actions, the variety of logical connections between them, the existence of "branching points" and the possibility to choose among alternative variants of supply chain process directions. In this chapter, the approach to the above-described assessment issue, called supply chain adaptation potential, will be considered.

9.1.2 Problem Statement

In this Chapter, we develop an approach to structural complexity analysis of supply chain designs based on the assessment of a supply chain's potential ability to adapt structurally in an agile environment. Figure 9.2 shows an example of a supply chain's structural configuration. Each operational block (sourcing, production, distribution, retail sales) contains a number of structural elements.

A supply chain structural model is a graph (or a network) of sourcing, production, distribution and retail operations within which knots correspond to processes

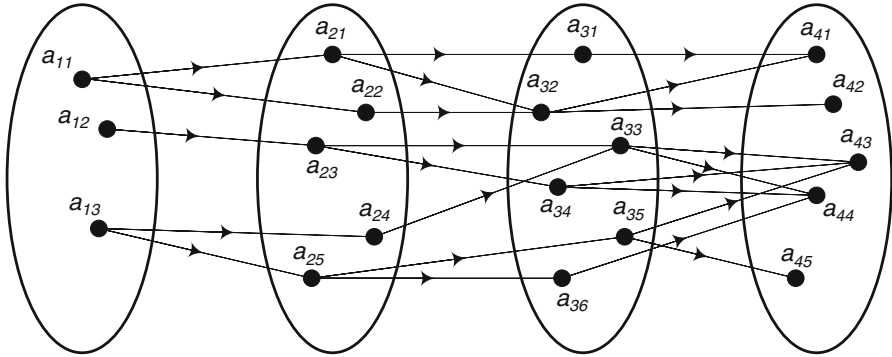


Fig. 9.2 An example of a supply chain's structural configuration (Ivanov and Arkhipov 2011)

and arches determine the logical sequence of process execution or their joint compatibility. Knots are allocated to the layers corresponding to operational blocks. Figure 9.2 shows that, in some knots, “branching” takes place, meaning the possibility to choose one of the admissible process directions. Each trajectory within the graph from one of the initial knots (actions at the first stage) to one of the final knots (actions at the last stage) represents a supply chain process that results in customer order execution. The network that is associated with the customers' orders represents, therefore, the alternative set or trajectories of the supply chain process realization.

We are interested in determining a new metric, supply chain adaptation potential and proposing a method for its assessment based on system entropy (Arkhipov and Ivanov 2011; Levner and Ptuskin 2017). This makes it possible to integrate the analysis of supply chain structure complexity and adaptability. Adaptation potential can be used as an additional indicator for selecting a supply chain structural design. The analysis of adaptation potential makes it possible to make a decision based on the determination of a number of elements in the supply chain, their variety and the interrelations between them with regard to the potential ability of a supply chain to adapt structurally in order to ensure flexibility and resilience.

9.2 Supply Chain Adaptation Potential

The concept of supply chain adaptation potential can be formulated as follows. *Adaptation potential* is the supply chain structural property which characterizes the decoupling or branching degree of supply chain execution processes and the possibilities of supply chain process execution adaptation to a real execution environment. This concept is close to the supply chain structural controllability approach modelled as spanned cactus (Lin 1974; Liu et al. 2011). We note that the supply chain characteristic called adaptation potential is a kind of general (abstract) characteristic, like the concept of uncertainty itself. Therefore, its quantitative

estimation should be perceived as a relative measure that has a local value in the context of the considered supply chain design problem. Due to this consideration, various approaches to the specified measure construction exist based on subjective considerations.

In this work, adaptation potential concept is introduced for estimating the supply chain's ability to compensate for the uncertainty level of its functioning conditions (predicted for a corresponding time interval) by using a multi-variant approach while selecting the trajectories of process realization development. If uncertainty conditions are formed under the influence of uncontrollable environmental factors, the adaptation potential is a kind of redundancy that is introduced into a supply chain to maintain the possibility of choosing alternative trajectories in the next operational block in the planning period, i.e., flexibility.

Taking into account the semantic affinity of uncertainty and adaptation potential concepts, it is proposed to use the entropy measure applied in statistical physics and the theory of information. Entropy is a measure of a complex system state's relative variety in the quantitative estimation of adaptation potential (Shannon and Weaver 1963; Lim 2007). Isik (2010), Durowoju et al. (2012) and Cheng et al. (2014) applied the entropy concept to analyze supply chain complexity and structural dynamics.

9.2.1 *Quantitative Estimation of Adaptation Potential: Basic Computation*

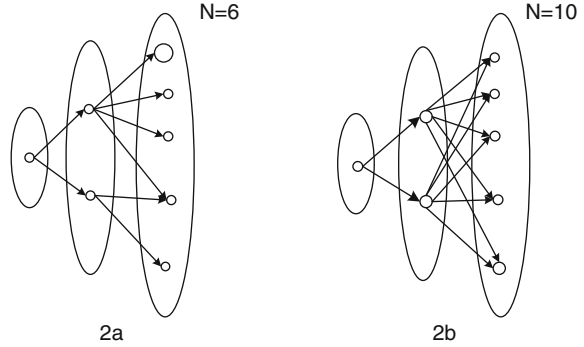
Let us assume that, for some demand forecasts, a network structure is designed and the planned period is generated and divided into T intervals. It is possible to choose between n_t supply chain elements within the t -interval of the planning period. Assume that a preference system of the supply chain structuring is unknown; therefore, the probability p of choosing any path in a supply chain is equal.

A set of objects and links between them in a supply chain represent a set of possible trajectories of supply chain process realization. Trajectories are designed according to the set system of logical links between adjacent time interval elements in the planning period. Network structural complexity as a measure of system process variety, equivalent to a variety of choices of alternative sets, can be estimated with the help of an indicator known as entropy H of a supply chain Eq. (9.1):

$$H = - \sum_{i=1}^N p_i \ln p_i \quad (9.1)$$

where p_i – probability of i -state of system or, in our case, selection probability of i -trajectory of process realization in a supply chain, $i = 1, 2, \dots, N$. In order to compute the entropy index H , first, the probabilities of each trajectory realization in the

Fig. 9.3 Examples of supply chain structures



supply chain should be determined and, second, the logarithm of this probability should be found. This will be explained further in a later section using a numerical example (see Fig. 9.2).

As the entropy assessment of supply chain complexity is performed as a basis for the further adaptation potential estimation, any of the log bases can be used. We use the natural (normal) $\ln$ because it is the most convenient way for computing experiments in entropy as shown in (Shannon and Weaver 1963).

It is not difficult to calculate the index of network entropy when the network is designed and the hypothesis about the choice of equally probable operations at each planning stage is accepted. As a result, an estimation can be received that indirectly characterizes the network adaptation potential. Let us consider a simple example (see Fig. 9.3).

Let a supply chain have the structure presented in Fig. 9.3a. For this network, the entropy index is $H = 1.74$ according to Eq. (9.1). There are two options to transit from the node of the initial stage to the 1st stage. Therefore, the probability is 0.5. In considering the upper node of the 1st stage, there are four alternative links to reach the 2nd stage. Therefore, the probability will be 0.25. Hence, the selection probability of each of the four ways through the upper node of the 1st stage is $p = 0.5 \times 0.25 = 0.125$. Now, the logarithm from this probability can be taken: $\ln 0.125 = 2.08$. We get $0.125 \times 2.08 = 0.26$. Since four alternative links exist, $0.26 \times 4 = 1.04$. Analogously, in considering the bottom node of the 1st stage, there are two alternative links to reach the 2nd stage. Therefore, the probability will be 0.5. Hence, the selection probability of each of the two ways through the upper node of the 1st stage is $p = 0.5 \times 0.5 = 0.25$. Now, the logarithm from this probability can be taken: $\ln 0.25 = 1.39$. We get $0.25 \times 1.39 = 0.35$. since two alternative links exist, $0.35 \times 2 = 0.7$. The sum of the two nodes in the 1st stage is, therefore, $1.04 + 0.7 = 1.74$.

The maximum value for a network with a set number of supply chain elements at each stage will be achieved when all the variants of transitions from i -operation elements to $(i + 1)$ -operation elements are admissible and equally probable (see Fig. 9.3b). For this case, we will have $H^{max} = 2.30$. For a network that has a more complex structure (see Fig. 9.2), the entropy index is $H = 4.52$.

In analyzing a real supply chain, it is useful to have relative (normal) estimations $H^{(o)}$ as well as absolute estimations of a variety level (entropy) H , previously having constructed a supply chain with the same quantity of elements of planned period stages (network knots), but with all the possible links between them and equal probabilities of all the trajectories: $H^{(o)} = H/H^{max}$. For the network in Fig. 9.3a, the relative estimation of entropy is $H^{(o)} = 1.74/2.30 = 0.76$. Absolute estimations allow us to compare supply chain structures that differ in the quantity of supply chain stages (the number of stages of suppliers, production, distribution, wholesalers, and retailers), the quantity of elements at each supply chain stage and a variety of links in between elements. The relative estimations characterize, in essence, the degree of affinity between the variety of links in a concrete supply chain to the maximum value.

However, the index (9.1) does not reflect one important supply chain structural characteristic – the maintenance of a high service level, which is important for the adaptation possibilities for the execution of customer orders. Processes in supply chain are always carried out under increasing uncertainty. Therefore, supply chain adaptation possibilities need to increase as supply chain process execution nears the customer.

The entropy index (9.1) does not reflect this idea. Let us introduce another supply chain structure, but with the same number of elements and links (see Fig. 9.4).

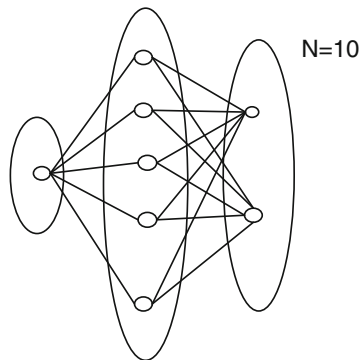
Indeed, the estimations calculated for networks, presented in Figs. 9.3b and 9.4, are identical and equal $H = 2.30$. At the same time, these two structures essentially differ, because the choice possibilities change in different ways while going to the end of the networks. It can be supposed that the heuristic estimation of the choice variety value for the supply chain presented in Fig. 9.3b should be higher, as it has more choice possibilities at the downstream stages than the supply chain shown in Fig. 9.4.

9.2.2 Quantitative Estimation of Adaptation Potential: Extension

An extended estimation can be received after some transformations of Eq. (9.1), considering each trajectory as a number of consecutive operational blocks (supply chain units) and, accordingly, presenting the i -trajectory selection probability as the multiplication of its units' probabilities $p_i = p_{i1} \times p_{i2} \times \dots \times p_{iT}$. Eq. (9.1) will be transformed as follows in Eq. (9.2):

$$H = \sum_{i=1}^N p_{i1} x p_{i2} x \dots x p_{iT} \ln (p_{i1} x p_{i2} \dots x p_{iT}) =$$

Fig. 9.4 Example of a supply chain structure



$$\begin{aligned}
 & \sum_{i=1}^N p_{i1} x p_{i2} x \dots x p_{iT} \ln(p_{i1} x p_{i2} \dots x p_{iT}) = \\
 & \sum_{i=1}^N \left(\prod_{\substack{k=0 \\ k \neq t \\ N}}^{T-1} p_{ik} x p_{it} \ln p_{it} + \prod_{\substack{k=0 \\ k \neq t \\ T-1}}^{T-1} p_{ik} x p_{i2} \ln p_{i2} + \dots + \prod_{\substack{k=0 \\ k \neq t \\ T-1}}^{T-1} p_{ik} x p_{ik} \ln p_{ik} \right) = \\
 & \sum_{i=1}^N \sum_{t=0}^{T-1} \left(\prod_{k=0}^{T-1} p_{ik} \right) x (p_{it} \ln p_{it}) \quad (9.2)
 \end{aligned}$$

In Eq. (9.2), symbol $\prod$ means the multiplication of i -trajectory units' probabilities except for one probability "connected" to the algorithm. As it can be observed in Eq. (9.2), supply chain variety is expressed through the probabilities of a trajectory unit's selection; each item, corresponding to a separate unit (or stage, which is the same in this case), is calculated like the entropy estimation. This allows us to introduce weights, which reflect the subjective considerations about the choice variety value at each planning period stage. We will designate these weights as w_t , and we will consider them normal as $0 \leq w_t \leq 1$, $\sum w_t = 1$. Let us call the obtained estimation the supply chain weighted variety (the weighted entropy) and designate it in Eq. (9.3) as H_w :

$$H_w = - \sum_{i=1}^N \sum_{t=0}^{T-1} w_t \left(\prod_{\substack{k=0 \\ k \neq t}}^{T-1} p_{ik} \right) x (p_{it} \ln p_{it}) \quad (9.3)$$

It is easy to show that after executing several simple transformations, Eq. (9.3) can be presented as shown in Eq. (9.4)

$$H_w = - \sum_{i=1}^N \sum_{t=0}^{T-1} w_t \left(\prod_{\substack{k=0 \\ k \neq t}}^{T-1} p_{ik} \right) x(p_{it} \ln p_{it}) \quad (9.4)$$

The index of weighted variety, calculated using Eq. (9.4), can also be named the supply chain *absolute adaptation potential*; we designate it as A and $A = H_w$.

For a supply chain with the maximum value of weighted entropy (this supply chain has the same quantity of actions as the initial network and the maximum number of equally probable trajectories), this formula becomes simpler as shown in Eq. (9.5).

$$H_w^{\max} = - \sum_{t=0}^{T-1} w_t \ln p_{it} \quad (9.5)$$

Let us consider the following estimation as the indicator of the supply chain's relative adaptation potential Eq. (9.6):

$$A^{(0)} = \frac{H_w}{H_w^{\max}} \quad (9.6)$$

In order to illustrate the proposed technique, we introduce several numerical examples. Supply chain structure variants are presented in Figs. 9.2, 9.3, 9.4, and 9.5; the necessary estimations of network variety and adaptation potential are shown in Table 9.1.

As it can be observed, the adaptation potential index is sensitive to a change in the supply chain knots (elements), the allocation of these knots within planning period intervals and the variety of variants in choice possibilities. Changes in supply chain potential estimations correspond to intuitive considerations about this indicator's dependence on the specified parameters.

Let us pay attention to absolute and relative potential estimation characteristics (see previous remarks on these indicators). In particular, we would like to note that the relative estimations with the maximum variety of links are identical and equal to 1, no matter how many stages and actions it has. This fact limits their application possibilities to a certain extent, but nevertheless they still keep their analytical role, supplementing absolute adaptation potential estimations. The proposed supply chain adaptation potential indicators can be used as criteria for selecting supply chain structures at the configuration stage.

Fig. 9.5 Example of a supply chain structure

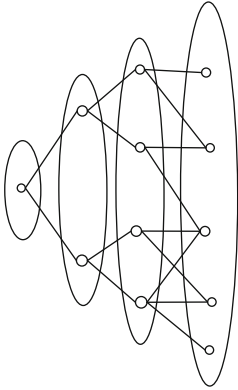


Table 9.1 Examples of supply chain variety and adaptation potential estimations for different network structures (weights w_t considered in direct proportion to the t interval number)

Structure variant (Fig. no)	Variety estimations, $H, (H^{max})$	Weighted variety estimation (absolute adaptation potential), $A = H_w$	Maximum estimation of weighted variety, H_w^{max}	Relative adaptation potential estimation, $A^{(o)}$
Figure 9.2	4.52; (6.11)	1.58	5.23	0.30
Figure 9.3a	1.74; (2.30)	0.94	1.31	0.72
Figure 9.3b	2.30; (2.30)	1.31	1.31	1.00
Figure 9.4	2.30; (2.30)	0.99	0.99	1.00
Figure 9.5	1.98; (3.69)	0.68	1.39	0.49

9.3 Adaptation Potential-Based-Identification of Methods for Supply Chain Design

Adaptation potential can be applied not only to analysis of a given supply chain structure, but also to the supply chain design itself. In this case, the supply chain design is subject to analysis of supply chain execution trajectories (i.e., order fulfillment lines). Trajectory synthesis and “optimum” selection can be organized in various ways. The key factor is the scale of the problem, i.e. the possible number of trajectories. If this number is insignificant, variant synthesis and the best variant search are rather simple procedures. The characteristic that defines the search scheme choice is the supply chain’s value for adaptation potential.

The maximum or close to maximum adaptation potential value shows the possibility of realization of (almost) all the trajectories: (almost) all elements (or executors) from different blocks are compatible. In this case, the most preferable trajectory variant can be generated from the leader suppliers, who rate first in the corresponding sequences. After this variant synthesis, it is necessary to check the compatibility of the suppliers that were included in a trajectory. If the compatibility condition does not hold (this is improbable for the considered case), it is necessary to make a trajectory correction (which will probably take several iterations) while

the specified condition is not executed. To accelerate the trajectory synthesis process, it is useful to conduct supplier selection by taking into account the logical links between them that reflect compatibility relations.

Let us consider now the case when the number of possible trajectories and the relative adaptation potential value are rather insignificant. In this case (which is the simplest for the analysis), it is possible to analyze *all* the trajectories and select the most preferable on the basis of their direct comparison.

The most difficult issue is selecting the trajectory when the number of variants is large enough (mainly because of the large number of supply chain operational blocks), and the value of adaptation potential, on the contrary, is low. This means that the supplier selection in various blocks “is strongly interconnected.” A rather small number of suppliers are compatible. To reveal the most compatible set using direct comparison is practically impossible because of their large quantity. At the same time, it is not possible to use the method of leader selection because there are not enough links in the given network model (suppliers–leaders and even suppliers with high utility function values will most probably appear incompatible). In this case, the decision can be found using the dynamic programming method. The proposed technique of substantiation of the planning trajectory search method is illustrated in Fig. 9.6.

- Zone I – application of the leader supplier selection method,
- Zone II – application of the direct trajectory comparison method,
- Zone III – application of the dynamic programming method.

Let us underline that the zone borders on the given diagram should be considered as indistinct and fuzzy. Figure 9.6 provides the following insights. If the network or its fragment estimations N_{max} and H are points inside zone I (far enough from its border with zone III, such as, for example, point A), the leader supplier selection method should be used.

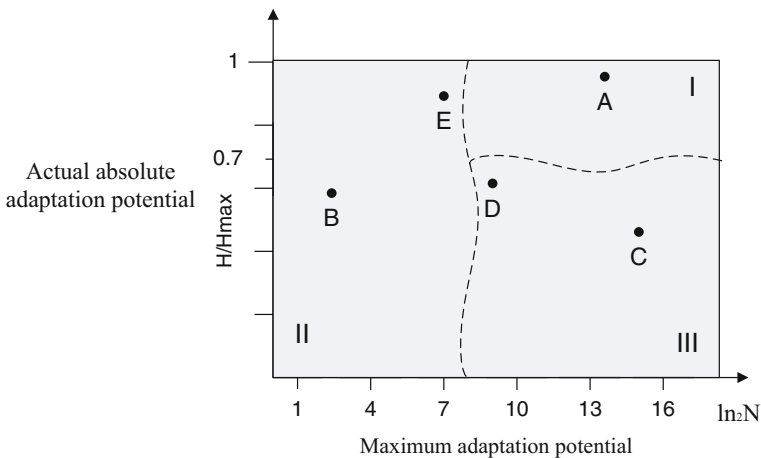
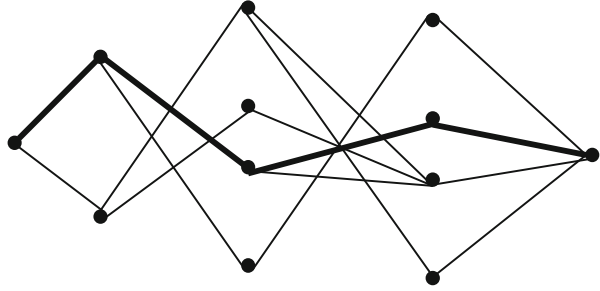


Fig. 9.6 Classification of “scale-adaptation potential” characteristics’ space for the selection of a method for supply chain design

Fig. 9.7 Supply chain structure with alternative trajectories of process execution



If the network or its fragment estimations N_{max} and H are points inside zone II (far enough from its border with zone III, such as, for example, point B), the direct trajectory comparison method should be used.

If the network or its fragment estimations N_{max} and H are points inside zone III (far enough from its border with zones I and II, such as, for example, point C), the dynamic programming method should be used.

If the network or its fragment estimations N_{max} and H are points in frontier areas (such as, for example, points D and E), additional analysis is required and additional approaches need to be elaborated.

Let us consider the example of an agile structure (Fig. 9.7).

The maximum quantity of trajectories under such allocation in blocks is: $N = 2 \times 4 \times 4 = 32$. The maximum (theoretical) adaptation potential value is: $H_{max} = \ln N = 3.47$. The actual absolute adaptation potential value for the given network model is: $H = 1.83$. The relative adaptation potential value is: $h = 0.53$. As can be observed, this value is insignificant. It means that only a small part of the theoretically possible links is realized in the model, and the leader selection method will probably not provide a viable result. In this case, it is recommended to apply the dynamic programming method to achieve the optimum planning trajectory.

9.4 Practical Aspects of the Adaptation Potential Calculation

The formulas offered in the previous paragraph for the adaptation potential calculation are rather simple and can be easily applied in computer programs. However, in the case of complex network models, technical difficulties may arise. In such situations, when the supply chain structure is “branched,” the number of trajectories can become astronomical. Accordingly, separate trajectory selection probabilities are very small and, as it is known, arithmetical calculations with small values lead to serious errors. That is why it is suggested to carry out the adaptation potential calculations on the basis of network model decomposition.

The analysis of various supply chain structures shows that the selection of a separate function realization technique within an operational block often does not

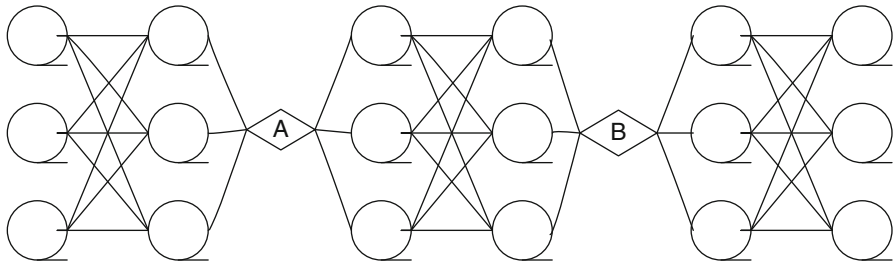


Fig. 9.8 Example of a supply chain with fictitious “dividing” elements *A* and *B*

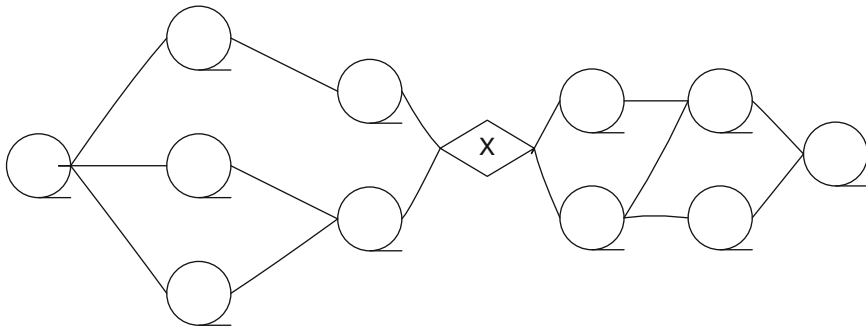


Fig. 9.9 Example of a supply chain with fictitious “dividing” action *X*

influence the element selection possibilities in other operational blocks. Such a situation is possible when all the possible links between the elements of adjacent blocks exist. In this case, the fictitious “dividing” block can be injected between these blocks, which include one element that divides the supply chain into two fragments. The supply chain adaptation potential estimation is approximately equal to the fragment potential sum. For supply chains that have the maximum number of links, this equality is exact, and it is possible to present this formally.

Let us consider several examples. We analyze a supply chain whose structure is illustrated in Fig. 9.8.

Let us introduce into this structure two fictitious “dividing” actions *A* and *B*, which divide the supply chain into three fragments, *I*, *II* and *III*. The supply chain and its fragments’ adaptation potentials are as follows: $H_{max} = \ln N = 6.59$, $H_I = \ln 9 = 2.197$, $H_{II} = \ln 9 = 2.197$, and $H_{III} = \ln 9 = 2.197$.

It can be observed that the equation $H_{max} = H_I + H_{II} + H_{III}$ is true.

Let us analyze the supply chain that has the structure shown in Fig. 9.9.

Introducing fictitious action *X*, we divide it into two fragments, *I* and *II*. The supply chain and its fragments’ potentials are as follows: $H_{max} = 2.01$, $H_I = 1.1$, and $H_{II} = 1.04$. In this case, the approximation takes place: $H_{max} = H_I + H_{II}$ (the error is 7%). We believe that the accuracy of calculations with network model decomposition is sufficient to carry out the real project analysis. Hence, it can be concluded that the adaptation potential estimation of supply chain fragments can be used to simplify practical calculations.

9.5 Estimation of Supply Chain Adaptation Potential Under Terms of Outsourcing

Let us consider a slightly different problem formulation. It implies estimating supply chain adaptation potential under the possibility of having alternative suppliers (outsourcing) at several stages (rather than selecting only one supplier for each stage). This is typical for the strategy of agility to respond to short-term changes in demand or supply quickly and to handle external disruptions smoothly. The study by Ivanov and Sokolov (2010) considered adaptive supply chains extended with the help of an additional *structural-functional reserve* of alternative suppliers to make the supply chain more responsive, flexible and changeable to mitigate demand fluctuations, to ensure customer-designed product realization and to recover supply chain operability in the case of disruptions.

The structural-functional reserve is a virtual pool of alternative resources (suppliers) that can be activated in accordance with dynamic changing requirements for supply chain performance and goals (Teich and Ivanov 2012). The structural-functional reserve can be applied to increase the above-mentioned attributes without additional costs in safety inventories, capacity and process coordination redundancies based on customer-synchronized collaboration and customer-oriented dynamic supply chain structuring. The pool of resources is the structural-functional reserve of supply chains. The structural-functional reserve increases the complexity, however, at the same time that it increases the adaptation potential.

The first step is network model decomposition (see Fig. 9.10).

A substantial analysis of operational blocks allows us to point out the following fragments in the network model structure: a fragment “Material delivery,” a fragment “Transportation and storage,” a fragment “Manufacturing,” and a fragment “Product distribution organization.” These fragments’ structures are shown in Figs. 9.11, 9.12, 9.13, and 9.14, respectively. Consistently connected fragments are typical of the general supply chain network model.

As mentioned above, we can consider the estimation of complex network adaptation potential equal to the sum of its consistently connected fragment potential with sufficient accuracy. Therefore, let us calculate the network fragment potential estimations for the analyzed supply chain. For this purpose, we apply the formula for calculating the maximum value of the supply chain trajectory variety and formulas for calculating the approximate network potential estimation. The calculation results are depicted in Table 9.2.

It can be observed from Table 9.2 that, in the case when approximate supply chain adaptation potential calculations are carried out without preliminary network model decomposition, we will receive an adaptation potential estimation equal to 19.8. The deviation is only 1%. Model decomposition, however, is useful not only because it simplifies the calculations, but also because it gives additional possibilities for analyzing the separate operational block and network fragment contributions to the general adaptation potential estimation. For example, it is possible to find out which supply chain design element selection narrows a further set of possible supply chain function realization variants that, at a certain point, reduces supply chain flexibility under any unforeseen factors, negatively influencing the supply chain in the future.

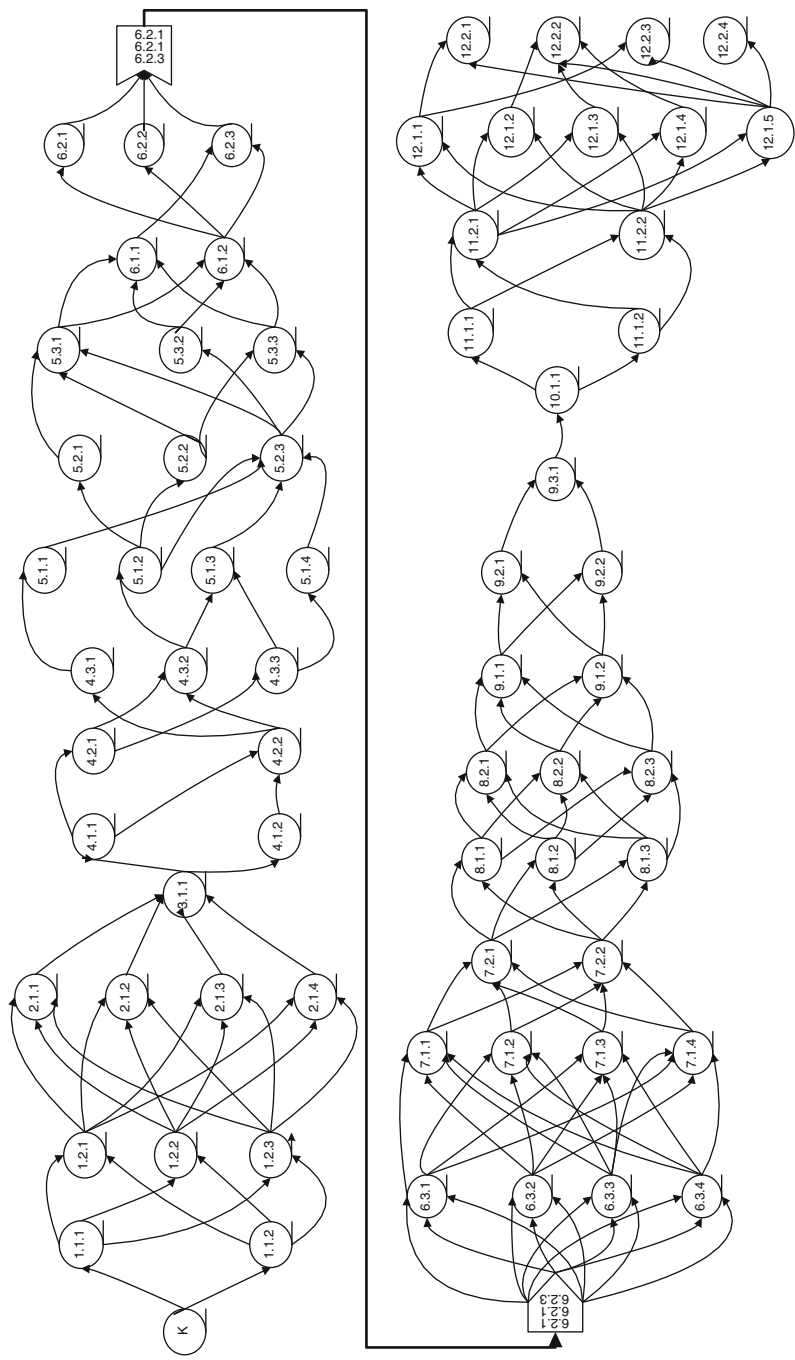


Fig. 9.10 Example of an alternative supply chain network model

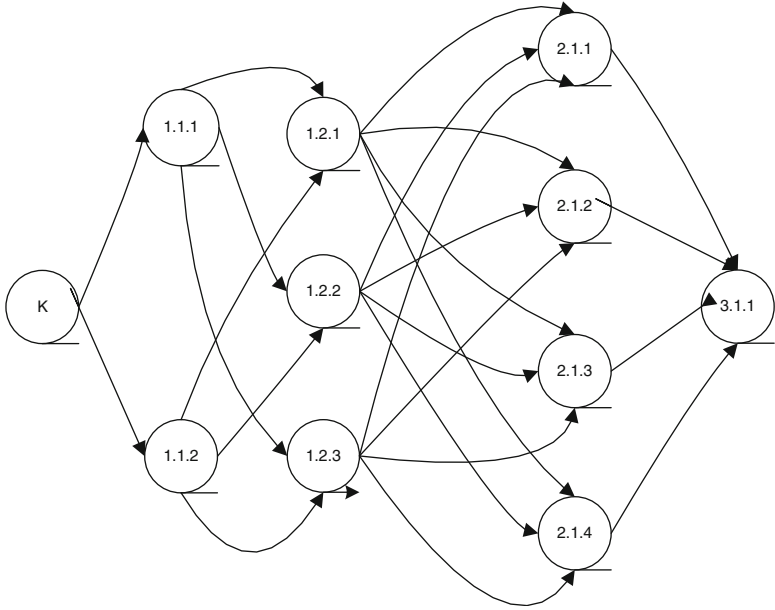


Fig. 9.11 Fragment “material delivery”

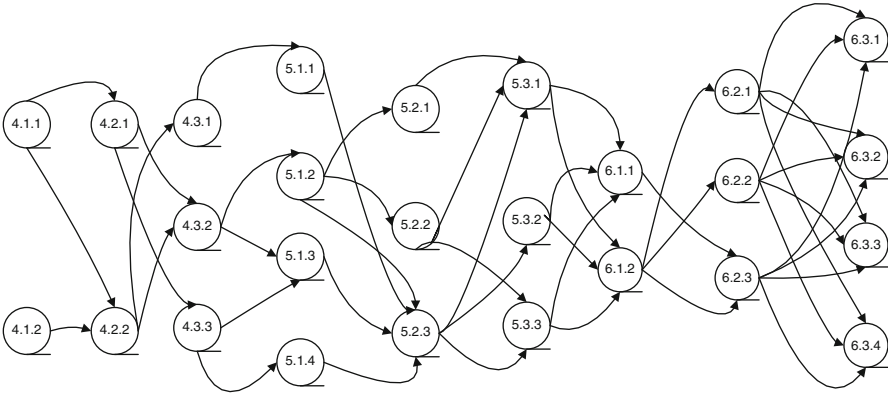


Fig. 9.12 Fragment “transportation and storage”

Speaking of the analyzed example, it can be observed that the supply chain considered has a rather high adaptation potential. The number of trajectories of reserved (i.e., redundant) processes is large, so this supply chain resilient can be considered resilient enough. The affinity of the adaptation potential estimation to the hypothetically possible (the deviation is 12.8%) provides evidence that the selection of elements in one operational block poorly influences the selection possibilities in other blocks. In other words, the supply chain operational structure, presented in its network model, is not too rigid. That seems to be the supply chain’s

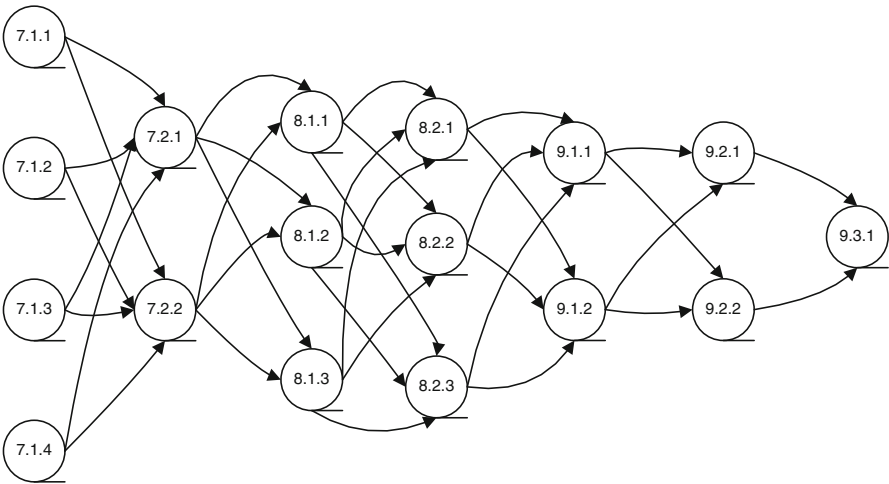


Fig. 9.13 Fragment “manufacturing”

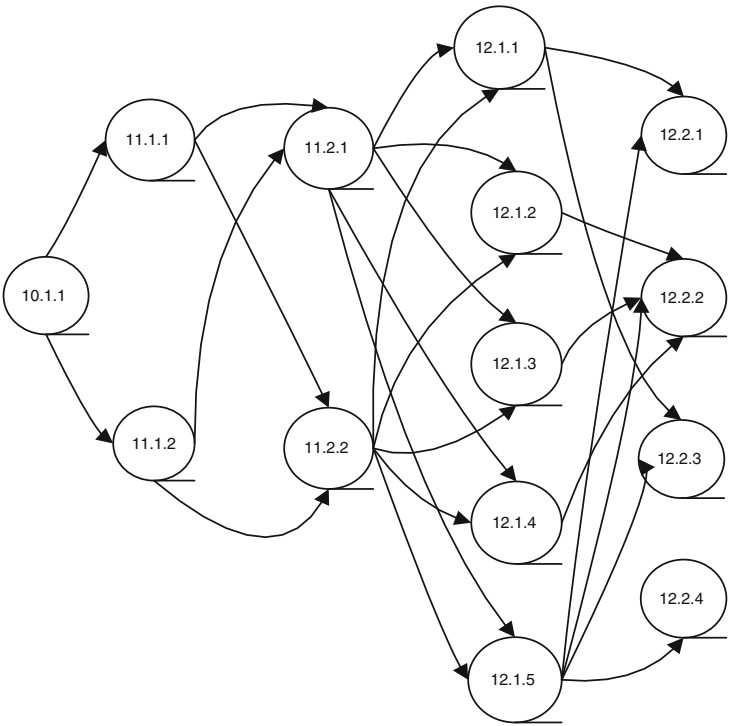


Fig. 9.14 Fragment “product distribution organization”

Table 9.2 Calculations of approximate supply chain adaptation potential

Supply chain fragment	Adaptation potential maximum value	Coherent index	Approximate adaptation potential estimation
“Material delivery”	3.18	1	3.18
“Transportation and storage”	9.25	0.74	6.85
“Manufacturing”	5.66	1	5.66
“Product distribution organization”	4.38	0.89	3.90
Supply chain			19.59

positive characteristic, because it creates conditions for an increase in flexibility in the supply chain network.

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Chapter 10

New Drivers for Supply Chain Structural Dynamics and Resilience: Sustainability, Industry 4.0, Self-Adaptation

10.1 Case Studies

10.1.1 Case Nissan: Resilient Supply Chain

Nissan Motor Co Ltd. was established in the 1930s in Japan and is dedicated to the automotive business. The natural disasters in Japan in March 2011 badly affected Nissan's supply chain. The Iwaki and Tochigi plants were almost ruined. Almost all production operations were stopped for many days. The Yokohama plant was able to recover its operation on 17 March, while the Iwaki and Tochigi plants were unable to relaunch production until 18 April (see Schmidt and Simchi-Levi 2013; Ivanov et al. 2017b).

However, despite the damage, even in 2011 Nissan was able to achieve positive growth and revenue. Global sales rose by 17.1%. Nissan had developed an extensive risk management program prior to March 2011. As early as 2010, a possible earthquake in Japan was timely forecasted and the response team had been built in advance. The team's responsibility was to gather information on the damage and take appropriate action to stabilize the situation and recover quickly. If necessary, a global and regional disaster headquarters could be set up to gather information about the facilities' conditions and business continuity. With suppliers, the business continuity plan was carried out by assessing the situation and prioritizing the actions to be taken.

The first priority was employee safety. The second priority was to prevent any further disasters, such as fire or stock damage. The third priority was to speed up recovery and develop the business continuity plan. The final priority was to contribute to society with cooperation and aid. Global and regional headquarters had been practicing simulation training to prepare in advance for a large-scale earthquake. Nissan carried out its disaster preparation and safety measures' exercise just 3 weeks before the disaster: this played a vital role in their speedy recovery.

Right after disaster struck, Nissan called for an immediate global disaster control meeting in 15 min in its Yokohama head office. The disaster committee members were already well aware of the severity of the disaster, as the shocks could be felt 100 miles away from the epicenter. The disaster committee started work on the recovery operations in each business location, subject to the safety and status of the employees, vendors and suppliers. Hundreds of employees from other facilities were dispatched to help restore damaged facilities. The global disaster control chief supervised all the operations and was closely monitoring recovery efforts in Japan while continuing operations abroad.

The recovery of Nissan's supply chain was faster than in other Japanese companies as Nissan was not part of the Keiretsu group and had diversified supplier sources and established a global procurement system. Nissan was free to choose parts suppliers whenever it need to. Nissan changed parts procurement and maintained production assembly outside of Japan and worked to overcome the impact of the disaster. The other reason for their quick recovery was that Nissan was holding higher inventory levels to boost sales at the time when disaster struck.

Three very essential actions determined the effectiveness of such disaster mitigation and recovery:

- being fully prepared for disaster,
- carrying out drills,
- going into action as quickly as possible after the disaster strikes.

Immediately after the disaster, Nissan called together factory managers from around the world to Japan in order to elaborate on the shortage of parts and logistics and avoid a collapse of global production. Nissan postponed all new development, cutting down on overtime for 3 months and almost all expenditure.

The following stages were included in Nissan's disaster management strategy:

- preparedness and assessment,
- setting priorities,
- empowering people,
- taking leadership.

First, Nissan created a contingency plan and assessed the damage to the operations. Second, priorities were set. The first priority was the safety of the employees; the second was turning normal pull production to push production to make sure that the products would be available on demand for customers, so that users would keep buying. Regarding communication and following recovery, each individual had to be aware of customer demand in the short run as well as in the long run. Communication had to be clear and simple to ensure that the plan to move forward into the future was sufficiently visible. Third, Nissan gave power to the employees working on the front line. Nissan enabled teams to make fast decisions to handle the situation, which ultimately helped towards a faster recovery. Fourth, leaders had to engage and commit. The leaders had to act as morale boosters and role models for staff, and to be authentically engaged and committed to the plan, since

employees would help to create and achieve the plan if leaders were with them in its implementation.

The results of the company's risk assessment, preparedness, actions and further business continuity were very impressive. The global disaster headquarters, Nissan technical center and Nissan advance technology centers were built to withstand disaster. Because of this, these facilities were among those buildings not impacted and Nissan used them to work on contingency plans.

Since March 2011, Nissan has been developing future strategies related to natural disasters. In March 2012, a simulation training was held based on a new scenario incorporating findings and new measures. One future strategy for supply chain resilience is to localize production of vehicles in the markets. For example, Nissan has forecasted procurement of 85% of local production of fully built units by the end of 2015 in the US. This reflects the company's other strategy: to decentralize its production from Japan. Lessons learned from the disaster were very clear – if another such disaster occurs, production in global facilities should not halt or be hampered. The decentralization strategy will benefit the company in two ways, since the strengthening of the Japanese Yen has been lowering the company's profitability. Nissan's disaster risk management strategy can be seen in the annual reports. It confirms that Nissan has been working on proactive disaster risk management strategies and is ready to handle any case that might arise.

Nissan has global as well as regional disaster headquarters, and clearly indicates which work and responsibilities belong to different departments, so that any disaster is handled in an efficient way. For example, the chief of the global disaster team will have current information about the situation of human resources, the control center, purchasing, and maintenance and service from the first response teams, while deputy chiefs of support and recovery actions will convey a report about the situation. Deputy chiefs will be in charge of regional disaster chiefs and will exchange reports and instructions. Each division has been given the authoritative power to take preventative measures to minimize the impacts of disaster.

10.1.2 Toyota: Supply Chain Disruption Management

A special focus of SCOM at Toyota is risk and disruption management (Marsh et al. 2011; Ivanov et al. 2017b). Many parts of Toyota's supply chain are located in areas that are likely to be hit by an earthquake. As such, the risk that Toyota's supply chain might suffer from those disasters is rising, and the damage may severely impact production and other activities. Given this scenario, it is essential to assume that Toyota itself, with its restricted resources, would be negatively impacted. For these reasons, Toyota is reassessing its business continuity plan and has made preparations to affect early recovery in the event of disaster. The foremost premise of Toyota's business continuity plan is to work on preparedness before and recovery after disaster happens.

As a part of *preparedness*, Toyota addressed the difficulty of “energy, information and transport network fragmentation” once disasters occur, and developed a hybrid car for the Miyagi Prefectural Police, installed with external power provision systems. In addition to providing good fuel efficiency and environmental performance in normal circumstances, during disasters these cars can be driven on fuel or electricity, and even have a power supply function that allows electricity to be drawn from the car.

Toyota’s help in *disaster recovery* areas is illustrated by the fact that they send their workers to production sites within the disaster affected areas, where they can engage in numerous activities such as restoring facilities and distributing disaster relief supplies. Worker volunteers from the Toyota Corporation continue to help with restoration efforts for individuals within the areas hardest hit by the latest disaster. Toyota additionally provides material support: trucks with relief supplies from the Toyota Corporation gathered at two local production sites.

Learning from such experiences, Toyota has prepared a nationwide framework for sending relief supplies to disaster affected areas which utilizes the warehouses and logistics network throughout Japan. In addition to stocking emergency supplies at the 34 distributors nationwide, Toyota has also built a framework for sending such relief supplies to distributors at disaster affected sites. Toyota attends to these relief supplies in order to deliver quick and reliable support for disaster affected sites, while taking into consideration such possible problems as motor fuel shortages.

The risk management committee at Toyota organizes meetings twice a year to identify the risks that may affect business activities and to take preventative actions against the negative impacts of those risks. The committee members include global chief risk officer (CRC), regional CRS’s and all senior managers and chief officers. They work to manage and prevent major risks in the regions and report on any immediate and serious disruptions.

10.1.3 Capacity Flexibility at Volkswagen

In 2011, new goals for 2018 for the Volkswagen Group were announced: 20% cost reduction; 50% fewer complaints about defects in new vehicles; 30 great innovations; higher employee satisfaction; perfectly trained workers; only 8 weeks between start and full operation of serial production – and all of this with 25% less environmental damage. These seven commandments had to be carried on an aluminum card by each VW production manager (Ivanov et al. 2017b).

The new Volkswagen production system (VPS) and the new logistics concept (NLK) at Volkswagen (VW)

Despite many achievements, the Volkswagen Group also faces many challenges concerning productivity, which is mainly influenced by production and logistics. While their biggest competitor, Toyota, produces, on average, 30 vehicles per employee each year, VW produces only 17.

Other challenges include different production processes at globally distributed VW locations, demand variations and missing flexibility in production and logistics, larger stocks as a consequence of separated production and logistics planning and the continuous development of new technologies (e.g., hybrid and electrical vehicles).

Toyota's success is based on lean production. Just-in-time (JIT) (no on-stock production and logistics), Kaizen (continuous improvement) and Jidoka (avoiding errors) are the three pillars of lean production. On the other hand for Volkswagen, the new production systems (VPS) and the new logistics concept (NLK) should improve production and logistics performance.

Through the new VPS-System, cost per vehicle should decrease by about €1500. This should be achieved through:

- introduction of flexible assembly lines, production of various models (e.g. the new VW plant in China can produce two different Golf models as well as two different Audi models on the same assembly line);
- standardization of production processes (e.g. one painting procedure for all 90 plants instead of 90 different ones as it is now the case);
- reduction in number of variations (e.g. only 28 variations of air-conditioning instead of 102 as is now the case).

The VW Group follows an ambitious strategy with VPS and faces great challenges. In the future, more models of different brands need to be produced in one factory to be able to react more flexibly. VW is, as of now in its factories in emerging markets, building models of Skoda, Audi and Volkswagen in one factory. This has never happened in the past. The logistics concepts of the last 20 years no longer fit here.

NLK is used on a broad basis at AUDI and in the overall Volkswagen Group. The aim is to optimize the supply process between suppliers and the Volkswagen Group. Through exact matching of supply schedules with shorter lead-times, improvement in the flow of goods will be achieved. Advantages for shipment handling on the supplier side will result in the following: shorter lead-times, better planning of production through "frozen periods" and a reduction in production materials.

In the past, VW used inventory to supply production. To be able to react to any demand from production, materials had to be stored. But if material sits without moving, no value is added in the case of VW. It is a waste which can be sustainably eliminated through the new system.

The idea is to make processes leaner and thus reduce lead times. The production and logistics processes need to be synchronized. If production has a cycle time of 1 min, meaning that every minute one vehicle leaves the assembly line, then VW will also apply this cycle time to logistics, from the line back to the supplier. This is new. One can imagine it working like this: there would be cycled traffic in the direction of the line to the material input. If there are 20 parts in a bin, the bin needs to be interchanged after exactly 20 cycles; VW needs to apply the same cycle time back to suppliers.

In the development of the concept and its implementation, all parties are intensively involved and make a substantial contribution. Collaboration with the factories' logisticians is very important. Mr Stein, head of the NLK project said (Automobil-Produktion (2014): "We are optimizing ourselves from inside to outside. We have a number of internal and external customer relationships within our processes, so the assembly line worker is a customer of the supplier. The optimized interaction within production was the starting point for consideration. We are speaking of a triangle; that means the assembly worker has a spot at the vehicle he is working on and a bin from which he gets the needed materials. Now the material availability is organized in a way where he literally does not have any walking routes and therefore the focus is on value-adding activities. Formerly, the materials were stored in multiple bins; today we are sequencing the material before sending it to the assembly line. This sorting is already happening, if possible, on the supplier side." Such a concept is called "supermarket." The materials are appor- tioned and prepared for each sequence in the line).

Next, information technology systems are also one of the success factors of the project. As the Volkswagen Group has focused on reducing lead time, it is necessary to adjust EDI (electronic data interchange) flow by planning exact pick-up and delivery times. This way, during a pick-up of the goods, the freight forwarder does not need to stop at only one supplier, but can make multiple stops along a fixed route (so-called milk runs). This process needs to be visible in the new EDI flow. New to the NLK process is the use of the order message system, EDIFACT GLOBAL DELJIT, which documents precisely the order process for goods.

This occurs in the following way. The *retrieval module* processes the preview received for production planning. It is used for a rough classification of the scheduled pick-ups. More detailed orders/fine planning are processed through dispatch calls. In the *JIT module*, the dispatch calls received are shown. An overview of all orders can be seen and printed out. The *JIT monitor* shows the orders, supervises them and tells the supplier when the next delivery is needed. On the JIT monitor information is split up in DELJIT by date and customer. The current delivery statuses are shown on the monitor and, in addition, provide information about all the materials delivered. Each delivery is announced through an EDI *delivery note*. The transfer of delivery notes should be made during the dispatch of transport by the supplier. The goods that are to be delivered are also to be marked with a goods' label. The former VDA4902 barcode label is replaced by the new *global transport label (GTL)*. In addition, there exist optional modules for direct connection to the ERP systems. Radio-frequency identification (RFID) is also employed in material logistics. As a result, the readability of active and passive transponders is excellent. However, it will be some time before there is broad implementation. The tags with which the bins have to be equipped are, at the moment, still too expensive.

The concept will be implemented step by step at all worldwide locations. Naturally, not everything can be achieved at once. The time frame is greatly influenced by product start in the factories. With a new product, new processes will also be used. Therefore, complete implementation will stretch over the coming

years. During this type of planning there is a program that is constantly changing, unlike a project which is completed after a few years. VW has started to optimize their in-house area, and now they are starting to step outside, into supply and transporting networking. Close collaboration with suppliers and service providers will change the processes, in- and outbound, step by step.

10.1.4 Volkswagen and Prevent Group Legal Dispute: Impact on the Supply Chain

In August 2016, the global car manufacturer *Volkswagen* had to stop its car production at several production facilities because of a dispute with two of its suppliers. Both responsible suppliers belong to the Bosnian Company *Prevent Group*. But not only the supplier group was criticized by public for its suspension of deliveries, VW also had to explain why they subject themselves to dependence on a few suppliers. In all, 22,000 vehicles could not be produced, which according to experts led to an overall cost of 100 million € (Welt [2017](#)).

For its models *Golf* and *Passat*, VW purchased seat covers from the supplier *Car Trim* while gear parts were bought from *ES Automobilguss*. Both suppliers accused the German car producer of recalling several orders without any cause or notice, without even paying a compensation fee (Manager Magazin [2016](#)). Consequently, both suppliers refused to supply VW with any materials. VW was forced to shut down several production processes at its main facility in Wolfsburg, as well as in other locations, such as Zwickau. The affected divisions were mostly assembly, body construction, painting and the press plant. After stopping several manufacturing processes, many employees' shifts were cut while logistic processes were shut down (Handelsblatt [2016](#)).

Both parties were able to come up with a solution to the conflict. Subsequently, the supply of production material started again and manufacturing facilities were reinstated step by step. The exact details of the settlement between both parties were not made public (Tagesspiegel [2016](#)).

The conflict had not only severe impacts on VW's production performance and business success, but also on the company's overall image. Politicians and media complained about VW burdening its employees as a consequence of this conflict. In total, 27,700 employees were not able to work according to their operation schedule (Wirtschaftswoche [2016](#)). As short-time allowances, which were paid during the production stop, are generally covered by an employee's social contributions, a lot of negative publicity has been published about the German car producer (Tagesspiegel [2016](#)). All in all, the given incident perfectly shows the severe impacts a strong dependency on a specific supplier can potentially have.

10.1.5 Case Study ASOS: Building Resilient Supply Chains Using Back-Up Facilities

A good example to display the importance of resilience in supply chains is the British online fashion retailer ASOS plc (Ivanov et al. 2017b). ASOS currently ships to 240 countries and operates one main global distribution center located in Barnsley (UK). Around 70% of the stock is held in Barnsley. The distribution center is crucial to ASOS as every item ASOS sells online is screened and checked there before it is shipped. ASOS also set up satellite warehouses and return centers in Ohio (USA), Sydney, China and Berlin.

On Friday, June 20, 2014 a fire at the central distribution center and warehouse in Barnsley (UK), which contained about ten million boxes of packaging, forced ASOS to cease trading. This is not the first time ASOS distribution was affected by a fire. Its previous warehouse in Hemel Hempstead was severely damaged after an oil blast at an oil depot in December 2005 just before ASOS entered the Christmas season. If we compare the two events and take into consideration that ASOS was a smaller company with fewer competitors, we can see that ASOS has since introduced business continuity management and has designed its supply chain to deal with disruptions.

The fire forced ASOS to take its website offline and to stop taking orders over the weekend. But they needed only 2 days to resume trading again though about 20% of total stock was destroyed. This is remarkable and proves that good risk management is in operation at ASOS and that ASOS learned from the fire incident in 2005. In comparison to 2005, ASOS's supply chain design structure included more warehouses. The layout of the main warehouse was re-designed and contingency plans were developed.

10.2 Disruption Risks Management and Supply Chain Sustainability

Structural dynamics is one of the underlying challenges in supply chain risk management and multiple dimensions of economic efficiency, risk management, and sustainability are interconnected in this research field. Supply chain resilience has a number of intersections with supply chain sustainability. This section aims to analyze sustainability factors which affect resilient supply chain structural design in regard to ripple effect mitigation and increasing sustainability.

Supply chain resilience issues extend far beyond risk management only. Methodical elaborations on the evaluation and understanding of low-frequency-high-impact disruptions are vital for understanding and further development of network-based supply concepts in a broader sense and from a cross-disciplinary perspective. One of the important interfaces is the design and management of resilient and sustainable supply chains (Linton et al. 2007; Carter and Rogers 2008).

Organizations extensively incorporate sustainability metrics into their supply chain management practices (Ahi and Searcy 2015). In this context, the development of models and decision supporting tools can improve decision-making about resilient and sustainable supply chains (Brandenburg and Rebs 2015; Giannakis and Papadopoulos 2016). The studies on supply chain sustainability differ across methodologies, but they commonly argue that the adoption of sustainable supply chains maintains business continuity to reduce long-term business risks. Business continuity is at the same time one of the fundamental characteristics of supply chain resilience.

Resilience has several intersections with supply chain sustainability (Derissen et al. 2011; Seuring 2013; Fahimnia et al. 2014; Ivanov 2017). Since supply chains have become more and more global, these network structures build the backbone of the modern economy and directly influence such sustainability issues as employment rates, natural resource consumption, etc. Important issues of supply chain sustainability are the assessment of supply chain design resilience and efficient supply chain structure reconfiguration in the event of disruptions from the perspectives of environmental, political and societal impacts.

Cost efficiency and waste minimization practices imply fewer stock points and storage areas along the supply chain. While such strategies may be environmentally sound and economically prudent, they may also inadvertently impact supply chain resilience given the limited availability of safety stock inventory to cope with supply and demand variations.

A portion of interesting mutual impacts can be expected in regard to single vs. dual/multiple sourcing. Sustainable sourcing practices may imply the need to purchase from and outsource to more sustainable suppliers only. However, the most sustainable supplier might be not the most efficient or robust supplier. Long term, trust-based relations with suppliers and securing steady employment relations in supply regions may collide with supply base flexibility for mitigating the ripple effect by dual/multiple sourcing and back-up facilities. In such cases, there might be multiple tradeoffs taking place between negative and positive effects. This relationship and issue affecting operational factors also has broader implications, such as the cascading effects of a lack of resilience or sustainability in the supply chain.

Academic research on sustainable supply chain design and management has been substantially developed over the past two decades (Seuring 2013; Fahimnia et al. 2014). Achievement of supply chain sustainability has been predominantly focused on reducing the environmental impacts of the supply chain, commonly measured in terms of greenhouse gas emissions and resource consumption (Gaussin et al. 2013; Seuring 2013). Seuring (2013) and Ahi and Searcy (2015) identify that sustainable supply chains aims at reduction of stock points and safety inventory in the supply chain and single sourcing practices with sustainable suppliers.

Simchi-Levi et al. (2015) considered the customer satisfaction aspect of supply chain sustainability and developed a risk-exposure index for the case of an automotive supply chain. The index computation is based on two models – time-to-recovery and time-to-survive – in order to assess the performance impact of a

disruption in the supply chain in terms of service level. The model identifies risk exposure at different suppliers and recommends proactive strategies for different suppliers in terms of performance impact and purchasing volume.

Ivanov et al. (2017a) considered return flow minimization in the supply chain driven by severe disruptions. The authors addressed the sustainability issue of waste reduction in the supply chain and developed a model to generate a resilient supply chain design and recovery actions.

The research on combined supply chain sustainability and resilience analysis is still at the beginning of its development (Fahimnia et al. 2014). Among others, the literature considers risks of severe accidents and recoverability along with customer satisfaction as important sustainability aspects (Ahi and Searcy 2015). Giannakis and Papadopoulos (2016) underlined the crucial role of risk management in supply chain sustainability. Brandenburg and Rebs (2015) analyzed the quantitative methods for supply chain sustainability. At the same time, the investigation of supply chain sustainability and resilience, together with the help of model-based decision support techniques, has yet to be explored in a focused and structured way. The mutual impacts and interfaces of sustainability on the overall resilience of the supply chain and the impact of resilience building practices on the sustainability performance of the supply chain has still remained unexplored (Fahimnia et al. 2015).

Ivanov (2017) studied the relationship between supply chain resilience and sustainability in regard to three hypothesis:

H1: Sustainable single sourcing enhances the ripple effect.

H2: Lower inventory enhances sustainability, but causes the ripple effect.

H3: Reinforcing major employers' facilities in regions mitigates the ripple effect and enhances sustainability.

The investigation results are summarized in Fig. 10.1.

Sustainable sourcing practices imply the selection of a single source supplier. However, the most sustainable supplier might be not the most efficient or robust supplier. Long-term trust-based relations with suppliers and securing steady employment relations in supply regions may inhibit supply base flexibility and decrease mitigation of the ripple effect by dual/multiple sourcing and backup facilities.

Cost efficiency and waste minimization practices imply less inventory along the supply chain. While such strategies may be environmentally sound and economically grounded, they may negatively impact supply chain resilience subject to limited availability of risk mitigation inventory to cope with disruptions.

Supply chain design structures and networking have a long-term nature; to a large extent they shape the labour market and employment developments regionally. In many cases, facilities represent major employers in a region. This is why it is mandatory to consider resilience and sustainability issues when designing supply chains comprised of such facilities.

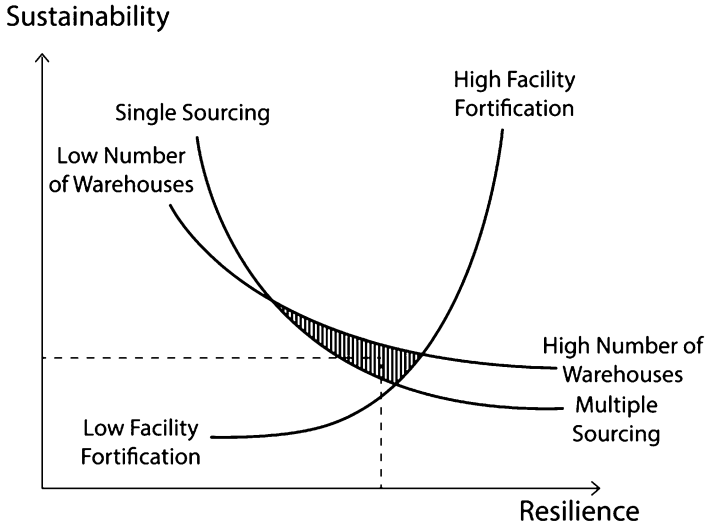


Fig. 10.1 Sustainability and resilience drivers in the supply chains

10.3 Structural Dynamics in the Framework of Industry 4.0

10.3.1 Industry 4.0 as a New Driver for Supply Chain Structural Dynamics

Individualization of products is part of critical business capabilities and requires flexible and customized production systems. Due to the increased complexity of flexible, small batch manufacturing, the costs of individualized production are typically higher than in mass production systems. Industry 4.0 technology enables new production strategies with the use of cyber-physical system principles that require highly customized assembly systems (Erol et al. 2015; Battaia et al. 2017; Battini et al. 2016; Kumar et al. 2016; Nayak et al. 2016). The ultimate objective of those systems is to facilitate flexible customized manufacturing at the costs of mass production.

Such innovative production strategies represent new challenges and opportunities for short-term job scheduling and sequencing. In particular, manufacturing processes for different customer orders may have individual station structures where flexible stations are able to execute different functions subject to individual sets of operations within the jobs (Weyer et al. 2015; Battaia et al. 2017; Ivanov et al. 2017a; Nayak et al. 2016; Zhong et al. 2017). Therefore, a problem of simultaneous structural-functional synthesis of the customized assembly system arises.

Practical environments for applications of scheduling and sequencing models and algorithms to simultaneous structural-functional synthesis of the customized

assembly system are multi-facet. With the help of smart sensors and plug-and-produce cyber-physical systems, the stations in the assembly system are capable of changing operation processing and setup sequences according to actual order incoming flows and capacity utilization (Otto et al. 2014; Theorin et al. 2017). In the FOUP (front opening unified pods) technology in the semiconductor industry, robots are used in real-time operation sequencing. Robots read information about the products from sensors and tags and decide flexibly where to forward a wafer batch next (Mönch et al. 2012).

Recent literature detailed principles and approaches for design and scheduling of flexible reconfigurable assembly systems with a focus on balancing, scheduling and sequencing (Boysen et al. 2007; Chube et al. 2012; Delorme et al. 2012; Battaia and Dolgui 2013; Battaia et al. 2017). In these studies, models and methods for solving problems related to the optimization of assembly system performance intensity for sets of flexibly intersecting operations have been presented.

It can be observed that in previous studies the selection of the process structure and respective station functionality for operations execution have been considered in isolation. In many real life problems, such an integration can have significant impact on process efficiency (Bukchin and Rubinovitz 2003). The problem of simultaneous structural-functional synthesis of the customized assembly system is still at the beginning of its investigation (Levin et al. 2016). Previously isolated insights into hybrid shop scheduling, scheduling and sequencing with alternative parallel machines can now be integrated in a unified framework. The three most important prerequisites for such an integration, i.e., data interchange between the product and stations, flexible stations dedicated to various technological operations, and real-time capacity utilization control, are enabled by Industry 4.0 technology.

Consider a customer system which interacts with an assembly system (Fig. 10.2).

The customer system generates orders (jobs), each of which has an individual sequence of technological operations. The interaction of customer and assembly systems results in alternatives for the manufacturing process design. Consider an assembly system composed of partially uniform stations, which are able to execute some technological operations. Each station has multiple channels, each of which is dedicated to a set of technological operations. Since multiple stations may perform the same operations, the alternatives of job scheduling and sequencing exists which are subject to actual capacity utilization, machine availability, time-related and cost-related parameters.

10.3.2 Vision of Adaptive Supply Chain Management Framework

In this section, we consider the *adaptive supply chain management framework* (Ivanov and Sokolov 2010). The *adaptation* is a comprehensive category defined

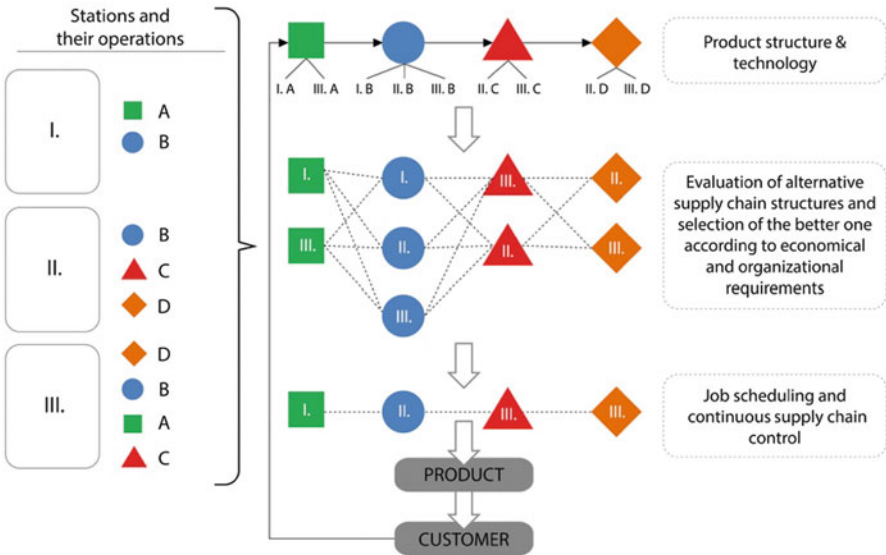


Fig. 10.2 Flexible supply chain structural configuration

in systems and control science that covers a system’s ability to change its behavior regarding changes in the execution environment and with regard to the system’s goals. The ability to change is the most important driver of competitiveness in modern and feature markets.

Moreover adaptation is the category that corresponds to the modern stage of state of the art management and information systems. Theoretical discussions on self-configuring and self-learning supply chains cannot be properly understood and implemented in practice with existing management systems and because of the lack of standard “mass” software solutions. However, in the future, adaptive supply chains should evolve into self-organizing and self-learning supply chains. The difference between *adaptive* and *self-organizing* supply chains is that in the adaptation approach the system’s shape and goals are fixed, while in self-organization both the system and its goals evolve. The system’s borders become fuzzy, the system can broaden by “acquiring” a space from the environment, or the system can narrow in a reverse way.

As a new research direction, *adaptive supply chain management* requires comprehensiveness in terms of the interrelations and consistency of conceptual business models, engineering frameworks, mathematical models and information technology. Recent research shows a gap between the engineering frameworks and mathematical models. Gaining advancements in this direction is a critical and timely issue because of the critical role of this level with regard to the practical applicability of business concepts and the development of information technology that would be adequate for business concepts.

In the further course of this chapter, we will consider a vision of the conceptual framework of *adaptive supply chain management*. In the subsequent chapters, the engineering and mathematical frameworks will be presented. These frameworks extend the narrow understanding of adaptive supply chains as mobile information technology or agent systems to a comprehensive new research direction that is composed of conceptual business research as well as model- and information technology-based advanced decision-making techniques in supply chain management.

10.3.2.1 Basic Terms and Definitions

In this section, the conceptual basics of the adaptive supply chain management approach are considered. We start with the main definitions, and then consider the adaptive supply chain management framework. Based on the frameworks of control and systems theory, let us introduce some basic definitions.

Definitions

Supply chain *adaptability* is the ability of a supply chain to change its behavior for the prevention, improvement or acquisition of new characteristics to achieve supply chain goals in environmental conditions that vary in time and the aprioristic information about which dynamics is incomplete.

Adaptive management is a management method of a supply chain with varying unknown environmental characteristics, in which for the final time defined (satisfactory, wished for, or optimum) goals of supply chain management are reached by means of a change in the supply chain parameters, processes and structures or characteristics of control influences on basis of a feedback loop.

Adaptive planning is a method of planning in which the plan of a supply chain is modified periodically by a change in the parameters of the supply chain or characteristics of control influences on the basis of information feedback about current, past or forecasted conditions in the supply chain.

An adaptive supply chain is a networked organization wherein a number of various enterprises

- collaborate (cooperate and coordinate) along the entire value-adding chain and product life cycle to acquire raw materials, convert these raw materials into specified final products, deliver these final products to retailers, design new products, and ensure post-production services; and
- apply all modern concepts and technologies to make supply chains stable, effective, responsive, flexible, robust, sustainable, cost-efficient and competitive in order to increase supply chain stability, customer satisfaction and decrease costs, resulting in increasing supply chain profitability.

Adaptive supply chain management studies the resources of enterprises and human decisions with regard to stability, adaptability and profitability of cross-enterprise collaboration processes to transform and use these resources in the most rational way along the entire value-adding chain and product life cycle, from customers to raw material suppliers, based on cooperation, coordination, agility and sustainability throughout.

10.3.2.2 Adaptive Supply Chain Management Framework

Various strategies of integrated production and logistics in industrial organizations – from supply chain management, virtual enterprise, agile/responsive supply chains and sustainable supply chains – have been developed over the last two decades. Although the strategies appear to differ in targets, presumptions, application areas, enabling technologies and research methodologies, each compliments the others, endeavoring to improve competitiveness. Considering the significance of all the strategies for organizations, the developed approach integrates elements of these strategies to develop a framework of *adaptive supply chain management* (see Fig. 10.3).

In the *adaptive supply chain management* framework, we do not set off different value chain strategies against each other, but consider them as an integrated framework. The encapsulation of the advantages of supply chain management, agility, and sustainability enables *adaptive supply chain management*.

Supply chain management serves as a basis for integration (organizational: suppliers and customers; functional: collaborative business processes; managerial: strategic, tactical, and operative decision-making levels), cooperation, and coordination. The strategies of *agility* enrich supply chain management by means of a general information space with the help of web services and higher flexibility/responsiveness through concentration on core competencies and building virtual alliances/environments. *Sustainable* supply chain management integrates the consideration of product development, utilization, product end-of-life and recovery processes. On the other hand, sustainable supply chain management brings into consideration policy and societal issues, which may affect supply chains and which may be affected by supply chains.

10.3.2.3 Adaptive Supply Chain Management Drivers and Organization

Figure 10.4 depicts the adaptive supply chain management strategy as drawn from elements of supply chain management, agility and sustainability.

In *adaptive supply chain management*, all three value chain drivers – products and their life cycles, customers and their orders, and suppliers/outsourcers – are enhanced by combining the elements from supply chain management, agility and

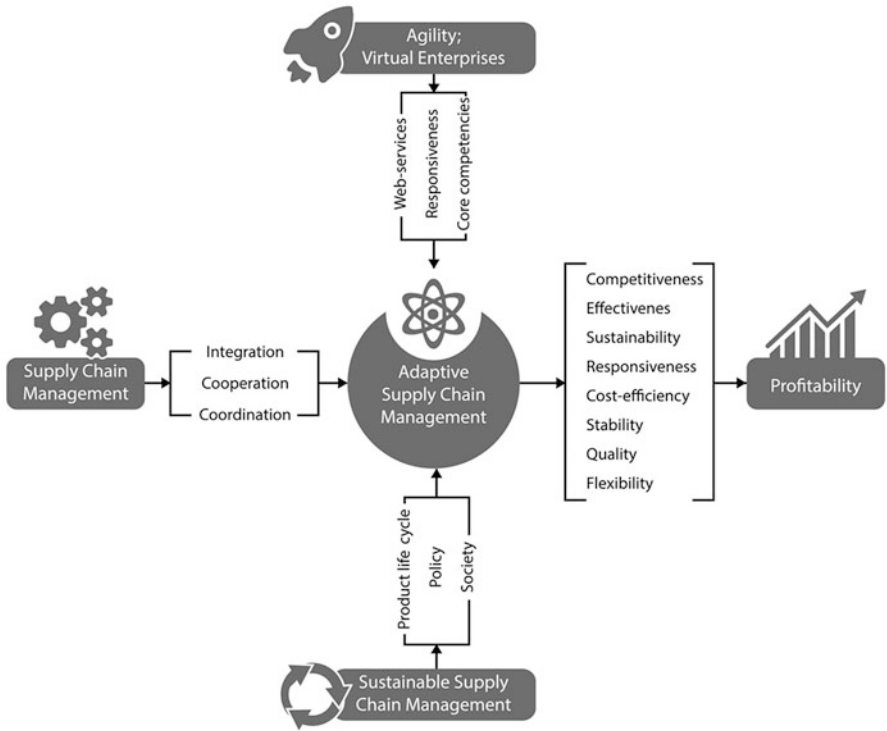


Fig. 10.3 Framework of *adaptive supply chain management*

sustainability. Moreover, these drivers are interlinked within a unified information space.

Adaptive supply chain management unites a supply chain control entity (an original equipment manufacturer (OEM) or a logistics service provider), customers and suppliers. The organizational structure consists of a real supply chain environment and a virtual alliance/partnership environment (see Fig. 10.5).

In the real supply chain environment, the supply chain owner collaborates with its customers and suppliers in terms of existing products and product lines in all the stages of the product life cycle. The virtual alliance/partnership environment is an adaptation structural–functional reserve of the real supply chain environment. In the case of market changes, new products, or an impact of operational inefficiencies due to a variety of disruptive factors (machine failures, human decision errors, information systems failure, cash-flow disruption or simply catastrophic events), these *structural–functional reserves* are activated to adapt the supply chain. Second, in the virtual alliance/partnership environment, new products are designed (with the integration of potential customers and suppliers).

In traditional supply chains, decisions about a customer’s order acceptance or rejection are made on a stable, long-term, predetermined supplier structure. In adaptive supply chain management, it is possible to build *new order-oriented*

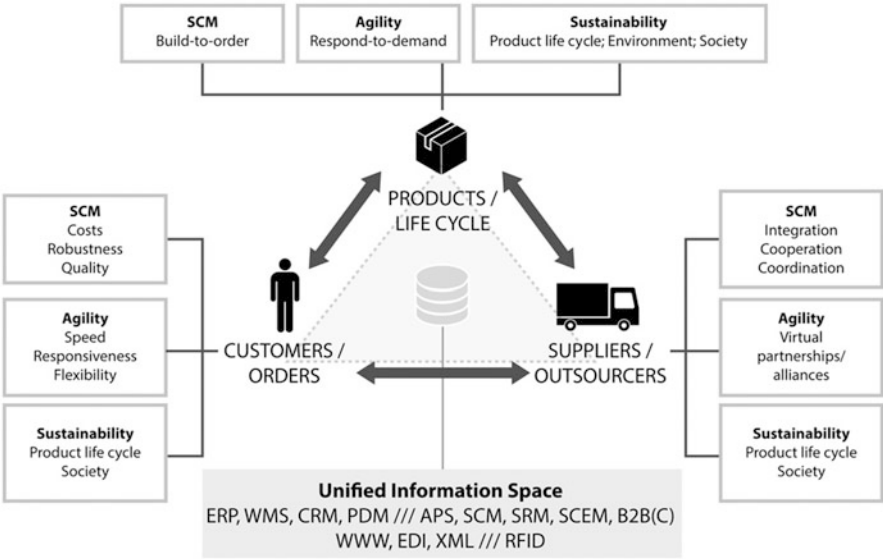


Fig. 10.4 Adaptive supply chain management drivers

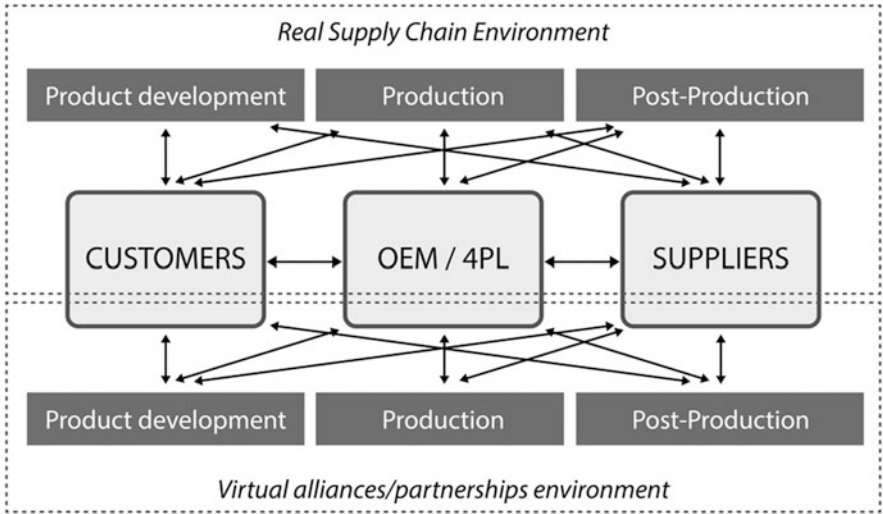


Fig. 10.5 Adaptive supply chain management organization

structures, taking into account technological product individualization, demand volume fluctuations or operative disruptions in supply chains (see Fig. 10.6).

Figure 10.6 depicts a case example from special machinery building. Similar cases can be found in the textile and or electronics industries. Supply chains are formed dynamically based on the offer parameters of the enterprises, customers’

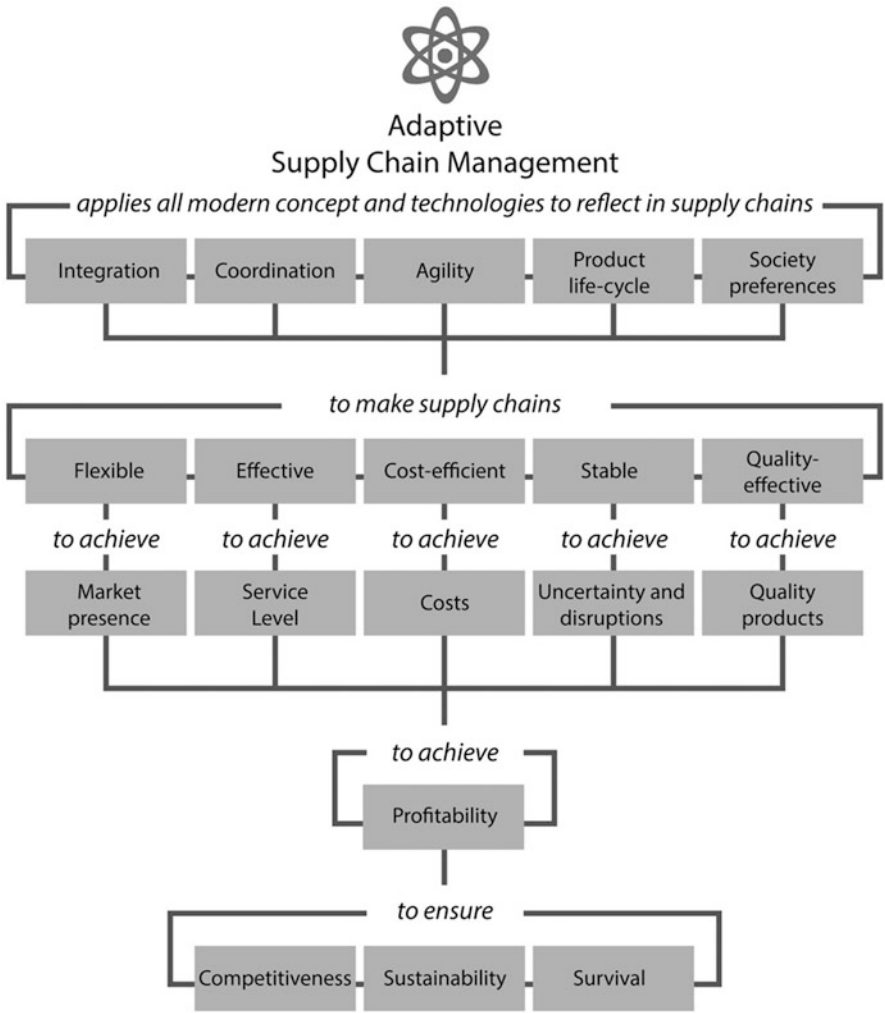


Fig. 10.7 Goal tree of adaptive supply chain management

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