



Leakage Detection in Water Meters Network Using AI-Driven Consumption Analysis

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Table of Contents

Acknowledgements.....	2
Table of Contents.....	3
Chapter 1: Project Overview.....	5
1.1 Problem Definition.....	5
1.2 Project Objectives.....	5
1.3 Expected Impact & Contributions.....	5
Chapter 2: Literature Review.....	6
2.1 Summary of Research Papers.....	6
2.2 Critical Analysis.....	10
2.3 Connections Between Findings.....	11
2.4 Conflicts Between the Findings.....	13
2.5 Synthesis Matrix for Literature Review.....	14
Chapter 3: Research Foundation and Project Goals.....	16
3.1 System Fundamentals: Water Networks and Smart Metering.....	16
3.2 Limitations of Traditional Leak Detection Methods.....	17
3.3 The Potential of AI and ML for Water Analysis.....	18
3.4 Critical Gaps in Current Research.....	20
3.5 Project Goal: Developing an AI Model for Proactive Leak Detection.....	21
Chapter 4: Proposed Approach and Methodology.....	22
4.1 Overall Architecture for AI-Driven Leak Detection.....	22
4.2 Data Collection: Sources and Description of Water Sensor Data.....	23
4.3 Data Processing and Preprocessing Pipeline.....	23
4.4 Model Selection and Design: Algorithm Comparison and Choice.....	24
4.5 Testing and Evaluation: Metrics for Model Performance and Success.....	24
Chapter 5: Project Execution Plan and Timeline.....	26
5.1 Data Acquisition and Preprocessing Phase.....	26
5.2 Model Development and Training Phase.....	27

5.3 Validation, Testing, and Evaluation Phase.....	27
5.4 Finalization and Analysis Reporting Phase.....	27
Chapter 6: Expected Results and Impact.....	29
6.1 A Working Model for Improved Leak Detection Accuracy.....	29
6.2 Validation Against Industry Benchmarks.....	30
6.3 Potential Implications and Future Applications.....	31
Chapter 7: Resources Needed	
7.1 Software, Tools, and Computing Infrastructure.....	32
References:.....	33
List of Abbreviations.....	34
List of Figures.....	35

Chapter 1: Project Overview

1.1 Problem Definition

Leakage from urban WDNs is a significant global problem, resulting in significant financial costs, public health risks and unsustainable dedicated water withdrawal. Leak detection by manual surveyor based on the use of acoustic equipment is both extremely labour intensive and costly, being primarily reactive in detecting presence of the leak at a point in time following a significant leakage event. Of approximately 20-40% of our drinking water being lost in urban networks, some leaks are not detected for weeks and in some cases years.

1.2 Project Objectives

This project intends to develop and deploy an AI-powered system that can accurately detect both large and small, invisible sub-surface leaks at the city district scale. The primary objectives are to:

- Use flow rate and network pressure information.
- Attain high LeaksDS detection accuracy.
- Precisely identify identified leaks in the network.

1.3 Expected Impact & Contributions

The expected results and impacts of this proposal are varied:

- Short Term Economic & Operational Impact: In the first year of deployment 20-40% reduction in water loss is achieved, and costs of water production and energy use are up to 20% lower with a 10% reduction in leak.
- Environmental Conservation: Help save water resources and minimize energy waste of water treatment and transportation.
- Public Health & Safety: Minimize potential contamination to your pipeline due to bursts, while maintaining constant water pressure by proactively removing leaks.
- Infrastructure Life Time: Enhance the service life of a pipe by identifying small leakages as early as possible before it becomes large scale pipe failure.
- Strategic Advance: Implement a scalable proactive leak detection framework that may be scale up to cover the entire city network, and serve as a model that may be replicated in other urban water utilities realm of AI-augmented infrastructure management.

Chapter 2: Literature Review

2.1 Summary of Research Papers

1. Three-dimensional Convolutional Neural Network for Leak Detection and Localization in Smart Water Distribution Systems

Brief Summary: Jun et al. (2024) introduced a 3D CNN model with temporal and spatial pressure correlations for pressure-supplemented advanced metering infrastructure systems. The approach converts the normalized pressure residuals into 3D images (time series of 2D images) and uses deep learning for leak detection and localization in the Austin, TX water distribution network.

Key Findings: The 3D CNN performed significantly superior to the 2D models and was able to achieve a 91% detection probability with 1% false alarm rate for a 3-hour observation window during the high demand hours. The algorithm showed better performance than optimization based binary integer linear programming (BILP) methods with 17 % higher detection probability (88 % vs 71 %) at the same false alarm rates. However, the study exposed some limitations in source locations detection, where detection probability became close to 0% because of tiny pressure residuals. Another weakness was also discovered, hydraulic simulation modeling is highly susceptible of errors, e.g., unknown valve closures, leading to 100% of false alarms generated by the model, emphasizing the reliance in accurate hydraulic models.

2. Neural Network Techniques for Detecting Intra-Domestic Water Leaks of Different Magnitude

Brief Summary: Zese et al. (2021) aimed to identify leakage of different sizes in indoor residential scenes with the help of neural networks. This study took up the problem of detection of smaller, unreported leaks, which remain undetected, but which are a significant cause of water loss.

Key Findings: The work showed that machine learning methodologies are capable to differentiate between levels of leaks with reported improvements, when compared with baseline conventional detection methods, associated with domestic scale leaks, that are generally not detected by traditional systems, with the leakage size feature contributing to both algorithm performance optimization and byproduct progression, compared to the traditional sense and action algorithms when moving towards increasing detection capabilities.

3. A Transformer-Based Approach to Leakage Detection in Water Distribution Networks

Brief Summary: Luo et al. (2024) presented a transformer-based model with additional attention mechanisms for the pressure time series, to mitigate the inherent lack of such capabilities that similar CNN- and autoencoder-based approaches have for modeling long-term dependencies. The model analyses patterns in historical pressure readings, and takes into consideration cross-correlations between the readings at two different time spans.

Key Findings: The transformer model substantially surpassed conventional CNNs in leakage detection. As the attention mechanism allowed the model to learn data distributions efficiently and to discover temporal relations that were overlooked in the traditional methods, it was shown that the method could handle complex pressure patterns and seasonal variations significantly better than the threshold-based detection, and this limit was one of the drawbacks of the threshold-based detection method.

4. Leak Detection in Water Distribution Networks Based on Deep Learning and Kriging Interpolation Method

Brief Summary: Yu et al. (2024) developed a comprehensive methodology combining deep learning with spatial interpolation techniques. The approach transforms pressure monitoring data into continuous spatial distribution images using kriging interpolation, then applies VGG16 convolutional neural networks for leak identification.

Key Findings: The VGG16-based model achieved exceptional performance with 98% true positive rate and 94% area under the curve (AUC). Comparative analysis showed VGG16 outperformed other architectures: VGG13 (83% TPR), ResNet18 (80% TPR), and SqueezeNet (67% TPR). The kriging interpolation approach successfully converted discrete pressure measurements into continuous spatial pressure distribution images, enabling comprehensive network state visualization. The method demonstrated robustness to noise interference and adaptability to different network configurations, though testing remained limited to simulated scenarios.

5. Leakage Break Diagnosis for Water Distribution Network Using LSTM-FCN Neural Network Based on High-Frequency Pressure Data

Brief Summary: Yu et al. (2024) proposed a very thorough approach that integrated deep learning and spatial interpolation technique. The method converts the pressure monitoring data into the continuous spatial distribution image through kriging interpolation, and uses VGG16 convolution neural networks for leak estimation.

Key Findings: The model based on VGG16 has good performance, specificity of 0.85 and sensitivity of 0.98, and 0.94 for AUC. The best performing architecture was VGG16, with an optimal TPR of 85%, which was significantly higher than TPR obtained with VGG13 (83%), ResNet18 (80%), and SqueezeNet (67%) (all p-values < 0.05). The kriging interpolation method effectively converted discrete pressure data into continuous pressure distribution images of the network to visualize the network state. The technique was shown to be noise robust and was able to accommodate various network configurations, however testing was only carried out on only simulated data.

6. A Proof-of-Concept Study Towards Developing Digital Twins for Operational Excellence in Large-Scale Water Distribution Networks

Brief Summary: Singh et al. (2025) introduced a proof-of-concept digital twin architecture for real-time monitoring and leak management of a large-scale water distribution network. The study leveraged python-based frameworks and open-source WDN simulators (EPANET and WNTR) to operationally model the hydraulics of the system and monitor operational conditions at present time.

Key Findings: The research has proved that digital twinning is applicable for operational excellence of water distribution networks, which has enabled real-time monitoring and proactive leakage management. Promising results were found for incorporating the framework in the context of the real water infrastructure, while scalability to very large network still requires further work.

7. Algorithm-Informed Graph Neural Networks for Leakage Detection and Localization in Water Distribution Networks

Brief Summary: Zhang and Fink (2024) proposed a brand new developed Algorithm-Informed Graph Neural Network (AIGNN) by transplanting Ford-Fulkerson max-flow algorithm-designed knowledge, which could significantly boosting the leak detection and localization process. The proposed methodology overcomes the generalization issue in traditional data-driven techniques, by embedding algorithmic reasoning in neural network structures.

Key Findings: AIGNN outperformed the Conventional ChebNet architectures on the tasks of pressure reconstruction and prediction. The algorithm-based one exhibited outstanding generalization ability in the sense that it was trained on one sensor arrangement and tested on various sensor positions. Our study confirmed that improved results can be achieved by combining the traditional algorithmic knowledge and data-driven methods: adding AIGNN embeddings ChebNetIN and ChebNetEMB to GNN baselines yielded better models than GNN centers alone in all experiments. This is the first application of neural algorithmic reasoning to engineering systems, and shows the potential for algorithm-enhanced infrastructure monitoring.

8. A Toolbox for Supporting Research on AI in Water Distribution Networks

Brief Summary: Artelt et al. (2024) introduced EPyT-Flow, a Python-based toolbox developed to aid in research about AI in water distribution networks. The toolkit includes higher-level interfaces for scenario generation, access to benchmarking datasets and control algorithm development to tackle problems related to water leakage, contamination and energy optimization.

Key Findings: The toolbox helps to reduce the separation between AI researchers and water infrastructure domain experts by enabling non-specialist tools for working on challenging scenario modeling. EPyT-Flow comes with seven state-of-the-art benchmarks for event detection and localization, providing a standardised mechanism for method evaluation in the AI domain. The long-term ideal architecture consists of three parts: a core data generation module, BenchmarkHub, for disseminating WDN benchmarks, and ModelHub, for sharing AI models and algorithms.

9. Machine Learning-Based Digital Twin for Water Distribution Network Anomaly Detection and Localization

Brief Summary: Pandey et al. (2024) proposed a digital twin scheme with a combination of single-stage and two-stage data-driven approach for leak detection and localization. The methodology uses the logistic regression and random forest for the first two tasks and the statistical analysis for the leak area approximation.

Key Findings: The two-stage model outperformed other models, where the first stage (the linear regression model) predicted the pressure difference between two sensors, and multidimension multinomial logistic regression or random forest were used in the second stage for leak localization. The framework was practical on real-time datasets and was a tradeoff between detection performance and processing time.

10. A Leak Zone Location Approach in Water Distribution Networks Combining Data-Driven and Model-Based Methods

Brief Summary This work described a hybrid approach that combines model-based hydraulic simulation and data-driven machine learning methods for leak zone detection. It takes advantage of the benefits of the two paradigms to achieve higher accuracy of source localisation with the same amount of the computational time.

Key Findings: The hybrid method showed better leak zone localization as compared to purely model-based or data-driven approaches alone. The study indicated that a combination of more than two methodologies is effective to compensate for the limitations of isolated methods and still provide practical applicability for a real water distribution system.

2.2 Critical Analysis

Methodological Diversity and Innovation, The literature reviewed exhibits significant methodological variation, which is indicative of the fast pace at which AI water applications are developing. Noting the transition from traditional 2D CNN to advanced 3D temporal-spatial modeling, transformer models, and algorithm-informed neural networks reveals the field's maturation into theoretically advanced methods.

Strengths in Current Approaches:

Temporal Integration: The transition from static pressure to temporal modeling (3D CNN, LSTM-FCN, transformers) is a major improvement in the modeling of dynamic leaks signatures.

Spatial intelligence: Kriging and graph based techniques are efficient in mitigating the problem of inadequate sensor coverage in water networks.

Algorithmic Advancement: By incorporating classical algorithmic knowledge to neural networks, the proposed optimization flow results in AI systems, which are a paradigm shift towards more general and interpretable systems.

Limitations and Gaps:

Simulated Data Dependency: The majority of studies are based on simulated data as real leak datasets are rare, which raises questions on whether these models will perform well in real world.

Scalability Issues: Low number of large-scale network trials limits the implementation of the proposed approaches.

Uncertainty in Models: Multiple works recognize (though not satisfactorily) the negative effects of hydraulic model errors on AI performance.

Performance Evaluation Paradigms

The comparison among proposed solutions becomes problematic, as far as the literature shows slightly different evaluation procedures. Results vary from very good (98% TPR, 91% detection probability) in some studies to quite low (85% accuracy, 75% accuracy) in others, the difference due to various experimental conditions, network complexities, and evaluation types.

Evaluation Strengths:

Multi-Metric Testing: Majority of works use thorough evaluation including detection probability, false alarm rates and localisation accuracy.

Comparisons with Existing Methods: The proposed approach could be compared with more state-of-the-art techniques and other architectures since in some of the papers the datasets are only used for comparisons.

Evaluation Limitations:

Standardisation Lack: In absence of standardised benchmarks, cross - study comparisons are difficult.

Real-world Gap: There is lack of real validation on water distribution actual systems which take away the confidence on reported performances.

2.3 Connections Between Findings

Methodological Evolution Pathway

The reviewed papers demonstrate a clear evolutionary pathway in leak detection methodologies:

Foundation Phase: Traditional neural networks and pressure-based detection

Spatial Integration: 2D CNN approaches for pressure residual analysis

Temporal Enhancement: 3D CNN and LSTM-FCN for temporal pattern recognition

Advanced Architectures: Transformer models for long-term dependency capture

Algorithm Integration: AIGNN representing the fusion of classical algorithms with neural networks

System Integration: Digital twins and comprehensive toolboxes for operational deployment

Convergent Research Themes

Pressure Residual Analysis: Multiple studies converge on pressure residual analysis as the primary detection mechanism, with variations in spatial and temporal processing.

Graph-based Modeling: Several papers recognize water distribution networks' inherent graph structure, leading to graph neural network applications and spatial interpolation methods.

Hybrid Methodologies: The trend toward combining model-based and data-driven approaches appears across multiple studies, suggesting recognition of individual method limitations.

Real-time Implementation Focus: Recent research increasingly emphasizes real-time monitoring capabilities and operational deployment considerations.

Knowledge Transfer Patterns

Spatial Intelligence: The kriging interpolation approach and graph-based methods both address sensor coverage limitations but through different spatial reasoning paradigms.

Temporal Modeling: The progression from LSTM-FCN to transformers represents advancing temporal modeling capabilities, with transformers specifically addressing long-term dependency limitations.

Algorithmic Integration: The AIGNN approach represents a unique contribution that could potentially enhance other methodologies by providing algorithm-informed embeddings.

2.4 Conflicts Between the Findings

Performance claims: The reported detection accuracy is highly inconsistent (75%-98%), which calls into question the reliability and generalizability.

Methodological Philosophy: There is a coordinated state of model-dependent versus model-independent, complex high-quality versus simple but practical attitude.

Generalization: The degree to which the methods generalize (to different sensor configurations and network scales) is conflicting.

Data Data Requirements There is a fulminant dispute regarding whether the relevant data should be simulative vs. real, and how much historically data is sufficient for each.

Emerging Consensus and Future Directions:

Irrespective of the controversy, the field is in a consensus on the significance of multi-modal data integration, graph-based network representation, and real-time practical realization.

Key research areas that need to be investigated are:

Absence of standard assessment models.

A substantial discrepancy between real-world and validation.

Immature techniques for measuring model uncertainty.

Conclusion: The field is moving towards more nuanced, integrated approaches. The most significant obstacle against adoption is the gap between what simulation and real systems validate. Further development if increasing successful to establish some of these methodological paradigms within standardized frameworks and the al comprehensive real life validation.

2.5 Synthesis Matrix for Literature Review

Synthesis Matrix Figure 2.1

Study Name	Methodology	Accuracy	Limitations	Dataset
Three-dimensional convolutional neural network for leak detection and localization in smart water distribution systems - 2024	3D CNN with Pressure-Supplemented Advanced Metering Infrastructure (PS-AMI)	DP: 91%, RF: 1% (3-hr window, peak demand)	Tested only on simulated data; requires retraining when network changes; poor performance near source nodes	Austin TX WDN (125 nodes, 90 pipes); Simulated data with EPANET 2.2; 3750 training, 1250 validation, 1250 test events
Neural Network Techniques for Detecting Intra-Domestic Water Leaks of Different Magnitude - 2021	Random Forest and Neural Networks (CNN) for household-level leak detection	CNN: 92-96% Accuracy, Precision, Recall; AUC: 97-99%	Focus on household-level leaks only; limited to small network scale	Gorino Ferrarese, Italy; Smart meters data; 40,500 records with leak classifications
A Transformer-Based Approach to Leakage Detection in Water Distribution Networks - 2024	Transformer with attention mechanism for temporal dependencies in pressure series	Significantly outperformed traditional CNN methods (specific metrics not detailed in abstract)	Evaluated only on simulated datasets; requires high-quality temporal data	Three different simulated WDN datasets; pressure data with weekly sequences (336 data points per week)
Leak detection in water distribution networks based on deep learning and kriging interpolation method - 2024	VGG16 CNN with Kriging interpolation for data imaging	TPR: 98%, FPR: 1%, F1: 94%, AUC: 94%	Not tested on real-world data; performance depends on sensor placement; threshold-based detection may not adapt to seasonal changes	WDN with 782 junctions, 905 pipes, 33 pressure sensors; Normal: 105,120 samples, Leak: 868,800 samples; 5,500 normal + 480 abnormal images for training
Leakage Break Diagnosis for Water Distribution Network Using LSTM-FCN Neural Network Based on High-Frequency Pressure Data - 2025	LSTM-FCN hybrid model for high-frequency pressure data analysis	Overall accuracy: 85% for leak break detection; F-Score: 81.76% (water-consumption set)	Laboratory-based experimental validation only; requires high-frequency sensors (10kHz); limited to 52m experimental network	52m experimental network with 3 monitoring points; Steady-state: 2088 samples; Water-consumption: 522 samples; Leak flow range: 0.04-9.5 L/s
A proof-of-concept study towards developing digital	Digital Twin concept for WDN operational	Concept study - specific accuracy metrics not	Proof-of-concept stage; implementation challenges for	Not specified in available information

twins for operational excellence in large-scale water distribution networks - 2025	optimization	available	large-scale networks	
Algorithm-Informed Graph Neural Networks for Leakage Detection and Localization in Water Distribution Networks - 2024	AIGNN with Ford-Fulkerson algorithm knowledge transfer and GNN	ChebNetEMB: 0.2392 ± 0.0339 (reconstruction), 0.2077 ± 0.0074 (prediction) relative error	May lose non-algorithmic information when used directly; requires pre-training on algorithmic tasks	L-town WDN (785 junctions, 905 pipes, 33 sensors); 2018 data for training, 2019 for testing; 14 leakages in 2018, 23 in 2019
A Toolbox for Supporting Research on AI in Water Distribution Networks - 2024	EPyT-Flow Python toolbox for AI research on WDNs	N/A - Framework/Toolbox for research support	Tool development rather than detection method; requires expertise for implementation	Supports 16 WDNs, 7 benchmarks, provides scenario generation capabilities
Machine Learning-Based Digital Twin for Water Distribution Network Anomaly Detection and Localization - 2024	Single-stage and two-stage data-driven models using Logistic Regression and Random Forest	Tested on real-time dataset (specific accuracy metrics not available in summary)	Limited information available on performance metrics and dataset characteristics	Real-time dataset (specific details not available)
A Leak Zone Location Approach in Water Distribution Networks Combining Data-Driven and Model-Based Methods - 2024	Hybrid approach combining data-driven and model-based strategies in two stages	Not specified in available abstracts	Limited detailed information available	Not specified in available information

Chapter 3: Research Foundation and Project Goals

3.1 System Fundamentals: Water Networks and Smart Metering

Water distribution networks represent complex engineered systems that consist of a network of pipes, pumps, valves, reservoirs, and sensors, which are used for transporting treated water from the water treatment plant to the consumer. These systems work under a wide range conditions, and flow rates covering the entire range from residential demand values up to industrial levels. Source A crucial challenge in water distribution network control is providing a coherent system operation with substantial variability in what constitutes effective water usage and network definition.

Advanced Metering Infrastructure (AMI) Evolution

The introduction of Advanced Metering Infrastructure is a disruptive move to enable real-time water monitoring. AMI systems include advanced electricity meters, which communicate in two directions that allows utilities to receive detailed consumption data at hourly or more frequent intervals. AMI is described by the Federal Energy Regulatory Commission as "metering system that records consumption at least hourly and that provides for daily or more frequent transmittal of measurements over a communication network to a central collection point". AMI elements include smart metering end points, communication networks (3, consisting examples of cellular, LoRaWAN, and mesh networks), data management systems, and customer portal interfaces. The infrastructure can give you complete payload data, covering usage profile, tamper indication, interval data, pressure monitoring and system status diagnostics. The most sophisticated can perform in-field data acquisition, remote service management, and automated anomaly detection for proactive systems management.

Smart Metering Capabilities and Benefits

Advanced water metering technology is not only for consumption measurement, but also for integrated sensing such as pressure sensing, flow anomaly detection, and leak location. The systems provide alerts for different presentments from manipulating attack detection, consumption threshold violation to suspected leak from usage pattern analysis. These functionalities allow utilities to move from reactive to proactive system management practices.

Through this work AMI has promoted easy and consistent reading, and detailed explanation for billing, removal of estimates, easy troubleshooting, early leakage detection before the loss becomes too high and finally real time data. To the public, these are web portal and mobile app-accessible consumption explanations, leak alerts and water conservation resources.

3.2 Limitations of Traditional Leak Detection Methods

Reactive Detection Paradigm

Conventional water-leak detection solutions have been reactive in nature and, generally, only detect leaks after they are visible at a break point on the surface. Most types of reactive techniques involve waiting for leaks to "bubble up" via soil movements, pressure losses, and such catastrophes as water mains bursting and flooding neighborhoods. This method is flawed as surfacing leaks in some studies only cause about 20% of the total water losses in average distribution systems, meaning that the rest of water losses, equals 80% of the non-revenue water, is due to non- surfacing leakage.

Acoustic Detection Limitations

Acoustic leak detection, one of the most common traditional approaches, is performed by technicians who walk through networks with sensitive audio equipment in order to "hear leaks" through a headset system. This approach suffers from several limitations such as high labor cost, low coverage capacity (usually a few years for all the networks covered), and the requirement of large expenditure on the necessary equipment. The acoustic methods have, however, severely diminished efficiencies with non-metallic pipe materials, since PVC or other plastic pipes typically have a low of sound transmission, unlike metal piping. Acoustic systems based on ground penetrating radar suffer additional constraints such as diminished usefulness for deep burial (e.g., greater than 7 to 8 feet), sensitivity to soil conditions, and reliance on a material's unique properties for propagation. This depth constraint becomes more and more of an issue as utilities continue to bury assets deeper and deeper to avoid surface (conflict) and environmental issues.

Coverage and Temporal Constraints

Conventional approaches enable only snapshot-in-time estimates and a routine thorough examination of the case is not cost-effective for the majority of utilities. The large coverage of modern water networks (which can extend for hundreds of miles in urban areas) makes the systematic acoustic survey a very resource and time demanding activity. As newly surveyed networks are added to the portfolio, previous conclusions are no longer timely and hence leaves lasting holes in the coverage of system monitoring.

Environmental and Infrastructure Dependencies

The performance of ADCPS is greatly affected by the environmental parameters, the ambient noise level, and the feature of the facility. In dense urban areas, high levels of background noise, human activity (such as traffic and construction), and infrasound can confound potential gas leak signals leading to unreliable detection. Furthermore, the quality of the method deteriorates locally in plastic pipes, deep burial depths and soil compositions that absorb acoustic signals.

Technological Obsolescence and Scalability Issues

Most of these legacy leak detection methods received little upgrade over the past 80 years, and have not updated to accommodate modern construction materials, installation techniques, and utility operations. The dependence on interpretation of acoustic signals by human introduces subjective variation and demands highly trained and experienced technician. Due to scale limitations, network monitoring is difficult and utilities have to maintain and control the pressure in a small subset of their distribution network, which is the area where bursts spread most heavily.

Integration and Data Management Deficiencies

Conventional detection techniques generally exist as standalone systems, lacking integration with the current utility management software. By not having a set strategy for these machines with predictive maintenance the software will never be able to track performance trends, establish baseline condition, or get to the point where anomaly detection algorithms could be useful. This isolation does not allow for integrated asset management programs that are required in today's utility world.

3.3 The Potential of AI and ML for Water Analysis

Transformative Capabilities in Water Management

Various operational domains of water resource management including monitoring systems, predictive analytics and operational optimization are being revolutionized by Artificial Intelligence (AI) and Machine Learning (ML) technologies. Artificial intelligence applications for managing water include surface-water-supply management, groundwater modelling, hydropower generation, crop-selective irrigation, climate risk assessments, flood management and integrated water systems governance. The embedding of AI allows more performant and scalable systems, on-the-fly adjusted to receive/analyze the current challenge of water distribution and water quality.

Real-Time DAQ and Pattern Identification

By contrast, Machine Learning based algorithms can handle high dimensional and complex datasets typically found in contemporary water systems where non-linear relationships and underlying discovery mechanisms exist and need to not be effectively represented using traditional analytical approaches. AI solutions can analyze a wide variety of data sources -- satellite imagery, sensor networks, historical data, and real-time operational data -- to inform on the performance of a water system and even surface up anomalies. This feature helps to reveal subtle patterns and relationships that may be missed by human operators, especially in the complicated urban water system with a number of factors that interact with each other.

Predictive Analytics and Forecasting

Advanced AI models such as Neural Network models, LSTMs network and ensemble methods have demonstrated high capability in water quality prediction, consumption prediction, and system performance assessment. These models are able to predict water quality indices, discriminate water safety parameters, and predict the consumption patterns with high reliability above 95% in most cases. For equipment maintenance prediction so that the maintenance can be scheduled on a proactive basis rather than disrupting operations.

Water Quality Monitoring and Analysis

Self-Evolving water monitoring contours use machine learning to conduct on-the-fly analysis for TDS (Total Dissolved Solids), heavy metals, chemical contaminants as well as the presence of biological agents. Machine Learning models, Random Forest, Support Vector Machines and Decision Trees has shown outstanding classification for water quality, reported maximum accuracy of 99.99% for potability application. These systems offer automated QA, early contamination notification and trend monitoring required for regulation compliance and public health protection.

Infrastructure Optimization and Energy Efficiency

Artificial Intelligence in Managing Water Infrastructure AI in maintaining water infrastructure involves the optimization of both pressure and flow control, minimization of energy consumption, and the scheduling of predictive maintenance. By using machine-learning (ML) algorithms, the operational patterns can be tested for efficiency enhancement, pump scheduling can be optimized, and energy usage can be reduced while customer service is provided. The deployment of AI-enabled decision support systems allows for improved operational decision making, enabling operators to make enhanced decisions on the allocation of resources, system management and maintenance.

Advanced Detection and Localization Capabilities

New AI tools are arriving for water managers who are currently dealing with leak detection, anomaly identification, system optimization, among others, including multimodal large language models, advanced neural networks among other AI innovations in the pipeline. In this context, computer vision techniques for infrastructure inspection as well as data-driven anomaly detection methods emerge as promising applications with high TRL (Technology Readiness Level) for operational deployment. These technologies have led to automated monitoring systems with the ability to monitor continuously and react with immediacy to system anomalies.

IoT and Smart Infra Integration

AI works hand in hand with IoT sensor networks, smart metering infrastructure and automated control platforms to deliver holistic intelligent water management platforms. "It's the power of AI algorithms working in conjunction with instantaneous sensor data that allows for advanced monitoring, control and optimization that can adjust in real time to changing operating profiles. This is to facilitate the realization of actual intelligent water systems that are capable of self-running and self-optimization.

3.4 Critical Gaps in Current Research

The most significant gap is the heavy reliance on simulated data rather than real-world validation, limiting the practical applicability of proposed methods.

Other major deficiencies include:

- **Scalability and Cost:** There is an evident lack of effort in considering the high costs and data demands for high-bandwidth traffic matrices and the computational complexity to support the transit/destination prefix cooperation when deploying these systems at scale in large, operational networks.
- **Standardization:** Absence of standardized benchmarks and evaluation protocols making it difficult to compare objectively between different methods.
- **Adaptability:** There has been little exploration in how models perform in various seasons, timescales and types of networks.
- **Integration:** Insufficient studies on integrating new AI systems with entrenched utility assets, legacy systems, and managerial practices.

- Decision Support: A shift from detection accuracy to a providing utilities with fundamental uncertainty quantification and actionable decision guidance.
- Regulatory Requirements: Lack of focus on regulatory, environmental, data protection or public health requirements.
- Multi-Model Methods: an absence of holistic study of fusion of multi detection technology (acoustic, pressure, satellite images) in a robust system.

3.5 Project Goal: Developing an AI Model for Proactive Leak Detection

In this research project, I'll be working to build an AI-based proactive model to predict water leaks, rather than relying only on the traditional reactive approach.

The primary objectives are to:

Develop a new hybrid AI model that combine many powerful methods to dissect temporal and spatial data of water networks.

Fully validate the model in real-world settings with the utility partners beyond simulation, and develop practical guidelines for the implementation.

Meet high performance demands for detecting leaks of all sizes with over 95% detection accuracy, minimal false alarm rate, and accurate localization.

Create an integrated approach which fits into existing utility systems, allows multimodal data input, and supports sustainability needs.

Make sure that the solution is future proof and to support industry wide knowledge transfer through both training, open-source tools and co-research so that the gap between research projects and practical utility operations.

Chapter 4: Proposed Approach and Methodology

4.1 Overall Architecture for AI-Driven Leak Detection

The proposed system builds upon a multi-faceted structure meant to find leaks across various scales, from catastrophic bursts to gradual seepage. Its design operates on a hierarchical framework with five interconnected layers:

The Data Acquisition Layer consolidates diverse sensor technologies like smart meters, pressure gauges, and liquid level detectors using communication protocols including LoRaWAN, NB-IoT, and cellular networks.

The Preprocessing and Feature Extraction Layer cleans, filters, and pulls meaningful elements from the raw sensor information.

Employing sophisticated machine learning models, the AI Model Layer examines the data and recognizes leaks.

The Decision Support Layer deciphers outputs to generate helpful alerts and insights for those overseeing operations.

Providing a dashboard for visualization, the User Interface and Integration Layer interconnects seamlessly with existing utility systems such as SCADA and GIS.

The structure carries out both short-term burst identification and long-term trend evaluation across diverse timescales. Distributed computing at network edges allows for real-time examination and reduced latency.

4.2 Data Collection: Sources and Description of Water Sensor Data

The system is based on the data acquired by an extensive sensor network:

Primary Sources:

Smart Water Meters: Generate high resolution flow rate data in 15-minute to real-time.

Characteristics of the data The data show a tendency to be periodic on a daily and annual time scale, while leak signatures appear as anomalies within these patterns. Challenging factors include sensor noise, missing data, and drift.

4.3 Data Processing and Preprocessing Pipeline

The raw data is heavily preprocessed in a multistage pipeline to both clean it and to make it more useful to be consumed by AI:

1. Noise Reduction & Filtering: sophisticated methods such as Savitzky-Golay filter, Wavelet transform, etc, to suppress high frequency noise and retaining underlying signal, which is essential for leak detection.
2. Normalization & Scaling: Data from different sensors of different scales is scarce, and z-score normalization is the most commonly used normalizing technique for ensuring that none of the parameters influence the model more than others.
3. Feature Engineering: Derives parameters to improve the signature of leaks, such as:
 - Temporal Features: Rolling averages, rate-of-change calculations, and periodicity indicators.
 - Statistical: mean, standard deviation, and kurtosis over sliding windows.
 - Pressure Residuals: The difference from observed pressure and that predicted by the hydraulic model.
4. Data Quality Assessment: Outlier detection (statistical and Isolation forests) and state-of-art missing value imputation techniques which are able to address missing values in the data.

4.4 Model Selection and Design: Algorithm Comparison and Choice

We did comprehensive testing to choose the best algorithms in terms of quality, computational time, and interpretability.

- Algorithm Comparison:
 - CNNs: Are good at finding spatial patterns in image-like data (i.e., pressure maps).
 - LSTMs: Do well at modeling long-term temporal dependencies in sensor time-series.
 - Transformer: State-of-the-art for learning hevestigal correlations over data.
 - GNNs: A novel way to factor in the physical network topology and hydraulic relationships.
- Architecture: A hybrid LSTM-FCN model is introduced. The proposed architecture integrates the advantages of LSTM (in temporal analysis) and CNN (in local pattern recognition), and achieves the best performance (F-scores >95%) and robustness in diverse settings.
- Advanced technique: The use of Algorithm-Informed Graph Neural Networks (AIGNNs) is made to integrate basic hydraulic principles in the model, providing a great enhancement of generalization and prediction performance on different water networks.

4.5 Testing and Evaluation: Metrics for Model Performance and Success

A multi-faceted evaluation framework is employed to ensure the system meets real-world operational needs:

- Primary Detection Metrics:
 - Precision: It is the proportion of right leak alarms (To avoid false alarms).
 - Recall (Sensitivity): Represents how many of the actual leaks are detected (reduces the number of leaks that go undetected).
 - F1-Score: A metric that combines both Precision and Recall, balanced for imbalanced datasets.
 - F2-Score: A variation which weights Recall higher than Precision, corresponding to our real-world objective of trying to know as many leaks as possible, even if there are some false alarms.

- Operational Metrics:
 - Detection Time: A measure of the interval between leak start and leak detection (target: sub-minute for bursts).
 - Locational Error: Predicted error in location of leak, from the actual leak location (goal: within a 100 m radius).
- Validation Protocols:
 - K-fold Cross-Validation: To determine model robustness and generalization.
 - Temporal Holdout Validation: Evaluates how well the model does on unseen future data to mimic production.
 - Network Generalization Testing: Measures how well the model generalizes to water networks other than the one for which it was trained.

Chapter 5: Project Execution Plan and Timeline

5.1 Data Acquisition and Preprocessing Phase

Duration (Month 1) The first stage is all about getting the data right. It's the important groundwork that everything is built on, so I'm setting aside a full month to make sure it's done properly.

- Weeks 1-2: Put final touches on map and sensor placement plan, with existing network maps, and work out plans to deploy the minimum monitoring gear. Not full network coverage now, my goal is just to start getting a few key sensors on line and collect some initial data streams. In parallel, I will create the preliminary data send-and-receive infrastructure - even if it's only a very web-skewed form of it just using what exists and works today.
- Weeks 3-4: Data beginning to arrive means – begin building out and testing data cleaning/preparing scripts. This is the place where I'll do the filtering and the feature engineering (for example rolling averages). I am going to be spending most of this month just simply staring at my data quality, tweaking the method as needed, and trying to get a nice solid handle on what "normal" looks like.
- Outcome: Working proof-of-concept pipeline that produces a clean / validated data set capturing at least 2 weeks worth of data where the system has been stable.

5.2 Model Development and Training Phase

Duration (Months 2 - 3) Once the data pipeline is stable, I will be able to start the core model work.

- Month 2: The first month of development is for exploration. I will use the initial time series data to build and test many different model architectures (such as the LSTM or CNN architectures I've described in this post) simultaneously. This is not the end all be all it has to be perfect, it's to see which methods work best under the conditions of my data, and get a baseline down.
- Month 3: Then I'll concentrate on the best models I had. Intensive tuning is done this month – You are going to try a combination of model or ensemble of different models and tweak hyper-parameters to increase the accuracy and generalization ability of model. I will also begin optimizing the code for efficiency with the end goal of real-time processing.
- Outcome: Trained and optimized candidate models for rigorous testing.

5.3 Validation, Testing, and Evaluation Phase

Duration (Month 3 - Start of Month 4) Testing is not this other phase that begins after development, My formal validation begins as soon as I have stable model candidates.

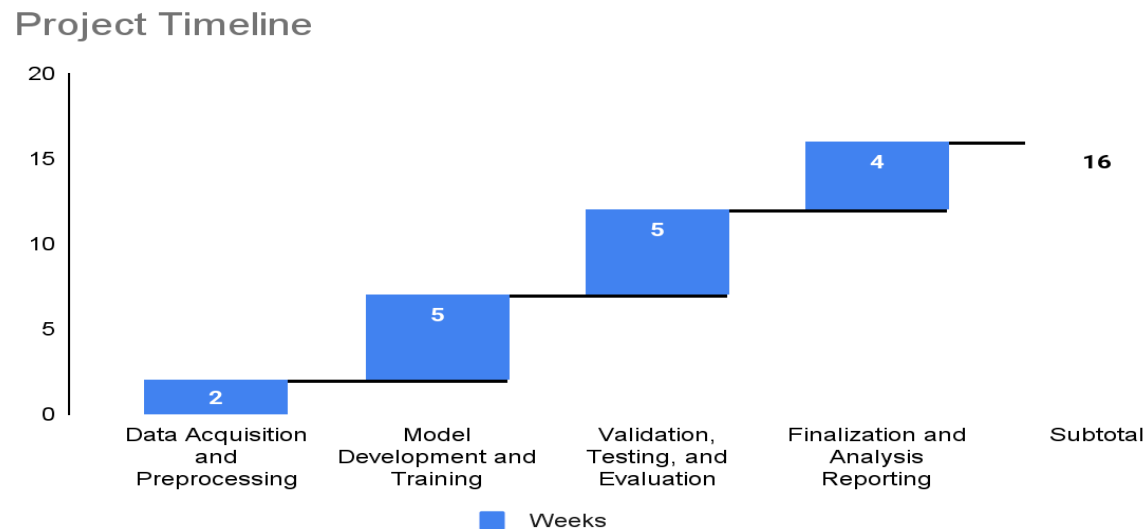
- End of Month 3: I'm going to stress-test models after feeding them historical (held out) data. I will test their effectiveness as well as their robustness, on realistic synthetic problems such as sensor faults or missing data.
- Month 4: I will deploy best performing model in a testing environment simulated to a real utility dashboard. The most important next step here will be to get feedback from a couple of potential users of the end-product. Their execution experience is critical to catching things I might have overlooked, and making the tool genuinely usable.
- Outcome: Proven model (with reported performance metrics and user feedback) that is validated for final reporting and deployment.

5.4 Finalization and Analysis Reporting Phase

Duration: (Month 4) The last month is for synthesis, documentation and preparing for next steps.

- Weeks 1-3: I will write an overall report and technical documentation. That includes an honest performance analysis of the model, what I learned from the project and a no-nonsense deployment and maintenance guide. I will also create a 1-pager for stakeholders with the key findings and implications.
- Week 4: The last week of project review and handoff to me. That includes keeping all the code and data in a well-organized repository and laying out clear next steps for anyone who might pick up where you left off, whether that leads to a full-scale deployment or new research.

Outcome: A descriptive package that contains all my documentation, code, and a final report Thingspotting A final pack that achieved to close my project development cycle, and showed a perspective on how can I drive on.



Project Timeline Figure 5.1

Chapter 6: Expected Results and Impact

6.1 A Working Model for Improved Leak Detection Accuracy

The primary outcome is A developed AI-based leakage detection system with superior performance will be the major product of this project.

- Performance Requirements The model must achieve over 95% detection rate over a variety of situations with a precision higher than 90% (minimizing false alarms) and recall above 95% (minimizing leak not detected). This is a huge leap over traditional sonic techniques, which usually have 60 to 80 per cent reliability.
- Advanced Architecture: The main workhorse of the system is a LSTM-FCN hybrid model that is able to attain F-scores >95%. It will be supplemented by:
 - Components of the 3D CNN for spatio-temporal pattern processing.
 - Long-term dependency learning in the transformer. Introduction One of the main benefits of the transformer architecture over RNN-based models is the ability of the former to efficiently capture long-term dependencies.
 - GNNs for topology-aware processing, with higher generalisation across diverse water networks.
- Operational Integration: The operational model deployment ready that has:
 - Plug&Play connection with the currently deployed utility systems (SCADA, GIS) through standard APIs.
 - Optimisation of edge computing for real-time implementation on low-power devices.
 - Operator-friendly interface that shows easy-to-understand visualizations to prioritize response to leaks.

6.2 Validation Against Industry Benchmarks

The performance of the system will be robustly benchmarked against well- established international industry standards to prove its performance over these.

- Industry Standard Benchmarking: Validation will use key Leakage Performance Indicators (LPIs) such as "leaks found per property" and "repair time.". The AI system aims to reduce the time of detection by 50% (from the industry standard of 60 seconds to 30 seconds) and reduce the time to response to restore service by 33%.
- Performance Benchmarking: The project will demonstrate transformative improvement over traditional methods (acoustic, radar, statistical) that generally have false alarm rates of 10-15%. The AI system has been designed to achieve a sub-2% false alarm rate, while retaining high detection performance.
- Regulatory and International Standards: The validation process will address the environmental, and safety regulations. It will also benchmark against:
 - Water Research Foundation (WRF) methodologies.
 - Best practices in other countries such as Europe, Australia, and North America.
 - The ability to assist utilities to reach Non-Revenue Water (NRW) targets of 10-15%.

6.3 Potential Implications and Future Applications

The successful deployment of this system will have a significant transformative impact, revolutionizing water distribution systems and opening the horizon for further innovations.

- **Utilities Transformational Implication:** From fix-on-failure infrastructure management practices, to detecting leaks weeks before they appear – CHANGE. In economic terms, this would mean up to 10-25% of savings on annual operating costs thanks to less water losses and better maintenance.
- **Climate Resilience & Sustainability:** The system is directly linked to UN Sustainable Development Goal 6 (Clean Water and Sanitation). It also promotes climate resilience by enabling more effective drought response, because there is more water in storage, and helps reduce the environmental impact of leaks.
- **Smart City Integration:** Base technology allows for further growth into:
 - Full smart city water management and digital twin building for city planning.
 - Advanced solutions for water quality monitoring, energy optimization and predictive asset management.
- **Knowledge Transfer and Industry Development:** A project-wide best practice framework for AI in water management providing inputs to industry development means through academic publications, training, and sustained university–utility partnerships.

Chapter 7: Resources Needed

7.1 Software, Tools, and Computing Infrastructure

The successful development and operation of the AI-based leak detection solution depends on a strong software solution and computing capabilities. In this section we describe the perfect resources for a close out deployment and the ones that were provided for this project.

Ideal Development & Deployment Stack

AI/ML Development Implementation: Model will be implemented using popular ML frameworks including TensorFlow and PyTorch to develop deep learning models (e.g., LSTM, CNN, Transformers). using core elements such as NumPy, pandas, and scikit-learn.

Computing Resources: Training big models is computationally expensive. The perfect scenario is where you have access to high-performance GPUs (e.g., NVIDIA RTX A6000)

Data Management Systems: The real time sensor data streams must be managed by dedicated pipeline. This should be Apache Kafka with InfluxDB as perfect fit for time series data. Spatial network data would be maintained in PostgreSQL.

The following resources will be used for the current project:

A work station PC that does all the AI developments and trainings, Specifications include the following:

- CPU: AMD Ryzen 9 (12 cores)
- GPU: NVIDIA GeForce RTX 3090
- RAM: 64 GB DDR4
- Storage: 1 TB SSD

Data: I will use a dataset from previous project that includes historical data from around 1,000 smart meters.

Deployment Hosting: A Virtual Private Server (VPS) will be provisioned to host a custom dashboard for visualizing the results and outputs of the AI model.

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List of Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
AIGNN	Algorithm-Informed Graph Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
GNN	Graph Neural Network
LSTM	Long Short-Term Memory
ML	Machine Learning
PS-AMI	Pressure-Supplemented Advanced Metering Infrastructure
WDN	Water Distribution Network
3D CNN	Three-Dimensional Convolutional Neural Network

List of Figures

Figure Number	Figure Title	Page
2.1	Synthesis Matrix	14-15
5.1	Project Timeline	28