

FORECASTING THE FUTURE IMPACT OF GAS EMISSIONS AND AIR POLLUTANTS ON THE ENVIRONMENTAL SUSTAINABILITY AND CLIMATE CHANGE

Literature Review

Literature survey demonstrates that there are several approaches to forecast air quality, reaching from numerical, mathematical, and statistical methods, to artificial intelligence practices, specifically Artificial Neural Networks (ANN). Forecasting and modeling of air quality and environmental constraints is of major importance for researches and has been done including several approaches, starting by atmospheric diffusion models to predict future emissions, or even the numerous statistical models that attempt to note the relationship between sets of raw data (or pre-processed original data) and target data. However, due to their lack of flexibility to convey the complexity and non-linearity of pollution and meteorological parameters' relationships, in addition to advancing technology and growing computer aided analysis procedures, Artificial Neural Network models proved useful and promising in handling complex and non-linear systems. Therefore, some of the work done on forecasting and predicting future emissions using ANN is presented in this chapter.

Junsub Yi and Victor R. Prybutok (1996) developed a feed-forward ANN using backpropagation algorithm and an architecture of 9 input neurons consisting of meteorological parameters (temperature, wind speed, wind direction) and vehicle emission measurements (CO_2 , NO_2 , NO , NO_x), 4 hidden neurons, and 1 output neuron representing ozone (O_3) predicted-levels. They compared the ANN model to regression and ARIMA statistical approaches. Their work suggested that the ANN model was superior to both statistical methods, and that the regression

model was more efficient than the ARIMA one. However, to come into such conclusion, care must be taken, and requires that both models, ANN and statistical, be built using exact data (Yi & Prybutok, 1996).

M. W. Gardner and S. R. Dorling (1998) in their work provide a review of the multilayer perceptron ANN, also known as the multi-layer feed-forward ANN and they present its applications in the atmospheric disciplines. They suggested that the neural networks are problematic to understand because there is no rule of thumb, or any rule at all, to decide on the neural structure, number of neurons or layers. Also, poor generalization that may arise due to overfitting of training data, and that could cause the network to suffer long-unneeded durations of training. However, they also demonstrate that the multilayer perceptron network can prove convenient for forecast, function estimation, and pattern classification when handling systems of non-linear structures that often cannot be explained with a full theoretical model, especially when trained properly (Grander & Dorling, 1998).

In their follow up work M.W. Gardner and S.R. Dorling (1999) developed multi-layer perceptron (MLP) models and compared it to linear regression (LR) models constructed by different authors (Shi and Harrison 1997) to forecast NO_2 and NO_x using meteorological

parameters. The MLP models' architecture consisted of 2 hidden layers with 20 neurons each using the scaled conjugate gradient algorithm as it is not sensitive to the choice of training indicators. They developed models with and without pollution levels as inputs in addition to the meteorological models. They found out that the ANN models with pollutant levels as input slightly outperformed the models without any explicit data regarding pollutant levels as predictors, however, all in all, the MLP ANN models outperformed the LR models. Also, they concluded that the emissions feature could be substituted by time-of-day indicators when using MLP networks without harming the performance of the network. Meaning that an absence of relatively significant input parameters does not necessarily limit the probability of developing a practical model given appropriate substitutions. They also noted, that in times of extreme episodes, the ANN models tended to underpredict the sternness of the incident (Gardner & Dorling, 1999).

P. Perez, et al. (2001) used a 3-layer feed-forward multi-layer perceptron neural network with a backpropagation algorithm to predict the PM_{2.5} levels in the air in the city of Santiago, Chile, for numerous hours in future using historic PM_{2.5} levels as inputs. They used the data between May and September as input data because this period showed most episodes of high PM_{2.5} concentrations. The model developed proved useful for predicting the future PM_{2.5} hours in the next hours in advance, however, they also showed that it may be possible to minimize the noise using another neural network specialized in filtering and smoothing the data set (Perez & Reyes, 2001).

Patricio Perez (2001) applied a multi-layer feed-forward neural network to predict the concentrations of SO₂ in Santiago, Chile. Several architectures were used to decide on the best model minimize the prediction error. The models were compared to regression and persistence models and showed superiority in predicting SO₂ values with reduced error. The study also showed

that using meteorological parameters (temperature, wind speed, relative humidity) is of great importance and significantly reduces the error of prediction. It also shows that after training the 3-layer neural network for the year of 1995 measures of SO₂, it was possible to produce a model to predict the data for 1996 using forecasted meteorological data (Perez P. , 2001).

Patricio Perez and Jorge Reyes (2002) employed a multi-layer feed-forward ANN model to predict the maximum of the next 24 hours average of PM10 levels using measured and predicted meteorological parameters, especially difference between min. and max. temperature, along with levels of PM10 measured until 6 PM on previous day. They used multiple architectures of ANN models and compared it to linear models. Even though, the ANN approach showed better performance, it was just a slight improvement that almost faded away when the PM10 levels exceeded 240 µg/m³. They showed that the selection of the input variables is more important than the verdict of choosing a linear or non-linear approach (Reyes & Perez, 2002).

Hamdy K. Elminir, and Hala Abdel-Galil (2006) utilized a multilayer feed-forward neural network of architecture 4:1:3 using backpropagation algorithm to forecast NO₂, PM10, and CO. They used meteorological parameters namely temperature, wind speed, wind direction, and relative humidity as inputs. They evaluated their model using RMSE and Mean Bias Error (MBE) and correlation factor to evaluate and test their predicted and observed values. The model achieved approximately 96% prediction accuracy, and 3.99%, 6.77%, and 3.82% RMSE for PM10, CO, and NO₂ correspondingly. The correlation factor obtained was 0.997, 0.969, and 0.978 for PM10, CO, and NO₂, consistently. The MBE indicated that the ANN model tended to overrate pollutant levels, but nevertheless, it remained in a range of errors that may be practical with acceptable-good prediction results (Elminir & Galil, 2006).

Lokman Hakan Tecer (2007) constructed 4 ANN models, 2 models per station, to predict the levels of SO₂ and Particulate Matter at 2 stations in Zonguldak, Turkey. Daily averages of pollutants for the year of 2002 along with meteorological parameters (relative humidity, temperature, wind speed, wind direction) were used and divided into training, testing, and validation data for the models. The ANN model used was a 3-layer recurrent (feedback) neural network based on backpropagation algorithm. The results effectively predicted the future measures of pollutants in the city. A regression model was used to validate the ANN models using the predicted values as input for the model. The determination factors for SO₂ at station 1 were 0.829, and 0.668 for training and testing sets, respectively, and 0.776, and 0.776 for station 2. For Particulate Matter, the determination factors at station 1 were 0.82, and 0.808, for training and testing sets, correspondingly, and 0.768, and 0.789 for station 2. These numbers explain the proportion of the inconsistency between observed and predicted values.

M. Caselli, et al. (2008) utilized a multi-layer feed-forward neural network with backpropagation algorithm to predict PM₁₀ concentrations using meteorological parameters (temperature, pressure, relative humidity, wind speed, precipitation) and PM₁₀ historic measurements at San Nicola station between Jan. 2005 and Mar. 2006. The model showed a 0.7 correlation between the predicted and observed data illustrating good performance of prediction. Also, the model was compared to a multivariate regression model that predicts PM₁₀ 2 days in advance and displayed that the neural network models outperforms conventional models such as the multivariate regression one. The authors also mentioned that the neural network performance can be improved with more inputs (Caselli, Trizio, Gennaro, & Ielpo, 2008).

Ghazi Sabri and Khadir Mohamed Tarek (2009) used meteorological indicators i.e temperature, wind speed, humidity, and real-time measurements of PM₁₀ and N₂ levels in a

recurrent ANN (NARX) model for prediction of multi-steps ahead of pollutant levels (PM10 & N₂) in Annaba, Algeria. They found that the NARX model outperformed the MLP (multi-layer feed-forward perceptron) model in short-term predictions and showed interesting results in long-term predictions. The 4-25-1 MLP model achieved a validation MSE of 1.7006 and a training MSE of 0.046, whereas the NARX model achieved 1.36 & 0.017, respectively, at a delay factor of 4 (Sabri & Khadir, 2009).

Atakan Kurt, et al. (2010) compared a non-geographic model to a geographic one for forecasting pollutant levels in a district in Istanbul, Turkey. Their non-geographic model is composed of a feed forward ANN with backpropagation algorithm using 10 inputs comprised of meteorological parameters and previous pollutant levels, 10 hidden neurons in a single hidden layer, and 1 output. They forecasted pollution levels for SO₂, PM10, and CO 3 days in advance, and the error ranged about 30%. They concluded that the geographic model outperforms the non-geographic one (Kurt & Oktay, 2010).

Abdel Karim Baareh (2013) used a multi-layer feed-forward ANN with a nonlinear sigmoid function and backpropagation algorithm for training to estimate the medium-term of the Carbon Dioxide gas emissions resulting from energy consumption based on global oil, natural gas, coal, and primary energy usage as inputs for the network. It was found out that the proposed network can estimate the CO₂ emissions with admirable outcomes (Baareh, 2013).

Mohammad Alkasassbeh, et al. (2013) exploited daily average meteorological parameters constructed from relative humidity, wind speed, and mean temperature to forecast PM10 and TSP (total air suspended particles) in the city of Al-Salt, Jordan over the period between November 2006 and November 2007. In their work, they used 2 NARX ANN models with architectures 7:3:1

for PM₁₀ and 7:5:1 for TSP. They used multiple criteria for evaluating the model including mean-square error (MSE), Euclidian distance (ED), Manhattan distance (MD), and mean magnitude of relative error (MMRE). They concluded that even though they trained the model based on a short-period input data, it performed with respectable results relative to the model evaluation criteria (Alkasassbeh, Sheta, Faris, & Turabieh, 2013).

M. Memarianfarad, et al. (2017) used a backpropagation feed-forward ANN consisting of 6 predictors, 6 neurons in a hidden layer, and 1 output to forecast PM_{2.5} in Tehran City using 3 meteorological constraints (Wind Speed, Humidity, and Temperature) along with SO₂, NO₂, and CO parameters. It was found that the use of this architecture of network yields the optimum performance with a MSE equal to 0.04943 and a regression factor of training, validation, and testing of about 0.658, 0.641, and 0.540, correspondingly (Memarianfard & Hatami, 2017).

P. A. Rahman, et al. (2017) used a multi-layer feed-forward ANN to predict the quality of air in an industrial city. In their work, they used 6 inputs combined from meteorological parameters and present value of pollution concentration, along with 2 hidden layers (11 neurons per layer) and a single output assigned to the forecasted pollutant level. They developed a tool that effectively predicts air pollution levels in the city of Sterlitamak, Russia, with an accuracy of over 70% (Safarov , Rahman, & Panchenko, 2017).

A. Sangeetha and T. Amudha (2018) used particle swarm optimization to estimate the CO₂ emissions in India based on coal, natural gas, oil, and primary energy, and compared it to multiple linear regression estimation model. They found that the particle swarm optimization is more accurate when compared to actual data. Then they forecasted the future emissions of carbon dioxide using ANN for the years 2017 to 2030. The objective of their work was to promote

awareness and offer foundation for policy making to address and reduce the ecological problems caused by CO₂ emissions (Sangeetha & Amudha, 2018).

Muhammad Azher Hassan and Zhaomin Dong (2018) forecasted Ozone (O₃) concentrations by utilizing previous measurements of NO₂ and meteorological indicators such as temperature, dew point, relative humidity, pressure, and wind speed. They adopted a multilayer perceptron approach and a general regression neural model (GRNM). Their study demonstrates that the MLP model performance is greater than that of GRNM one with correlation coefficient values of 0.91 for MLP and 0.76 for GRNM between predictors and predicted output. Also, their validation criteria based on Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) shows that for both criteria the MLP performs better than the GRNM with 21.74 and 14.22 for MLP, and 26.94 and 16.42 for GRNM. In addition, the authors suggested that dew point and relative humidity are the most important indicators when forecasting O₃ using meteorological parameters (Azher Hassan & Dong, 2018).

The contribution of this work is to utilize the pollutants concentrations and meteorological parameters' measurements data acquired from the MoEnv air quality system stations, 4 stations in specific, to forecast the future concentrations of air pollution in the city of Amman, Jordan. To the best of the author's knowledge, this work has not been previously conducted.

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