43 Artificial Neural Networks in Forecasting Key Air Pollutant Factors in Public and Environmental Management

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The application of artificial neural networks in various fields has been increased the last years with the development of new neural network learning techniques and tools for developing neural network models. This paper studies the construction of artificial neural network models in order to predict key air pollutants. Forecasting air pollutants is vital in the environmental and public management and planning since it can be used in preventing environmental degradation and also in protecting human life by helping the authorities to take proactive measures. The levels of air pollution parameters were chosen to be predicted, since these factors are related with human health problems especially respiratory deceases. Multiple artificial neural network models were constructed by using different architectures regarding the number of the neurons in hidden layers, the number of the hidden layers and also the transfer functions in order to build the optimal model that would forecast efficiently the levels of air pollution factors. The Multilayer Feedforward Perceptron was utilized in this research since it is the most suitable for time series forecasting according to the literature. The proposed methodology can be valuable in public administration, since it can be used as a decision tool for applying more efficient environmental management practices and also in adopting sustainable decision making strategies.
Keywords: Artificial Intelligence; Neural Networks; Environmental Management; Public Management.

43.1 Introduction

The natural environmental conditions affect thoroughly the quality of human life. Especially, air pollution has negative impact on human health since it is connected to various diseases such as respiratory irritations, infections and other kinds of health problems [1][2][3].
The associations between mortality and environmental air pollution has been examined by several researchers [4][5]. A research [4] has showed that the total mortality was substantially associated with carbon monoxide and nitrogen dioxide air concentrations and weekly connected with sulfur dioxide and Particulate Matter 10 (PM10) concentrations.

Another research [5] has showed that mortality is positively associated with deaths caused by lung cancer and also by cardiopulmonary diseases. The same study has shown that total mortality was strongly associated with air pollution.
The significance of air pollution information is very high in environmental management and planning since environmental pollution is connected to environmental degradation.
Furthermore, data regarding air pollution must be studied by the authorities in order to adopt the most adequate environmental policies so as to protect the human health and also the environment, the natural habitats and to prevent the environmental degradation [6][7].
Environmental data regarding air pollutant factors can play a significant role in public management and also in environmental decision making by promoting sustainable management and planning strategies [8][9].
Information and Communication Technology has been applied in several sectors of environmental management [10]. Artificial neural networks have been applied in many scientific fields. New neural network based technologies and programming tools has rapidly increased the application of artificial intelligence in multiple sectors [11][12][13][14].
A research [13] has examined the forecasting of two important air pollutant factors: ozone and nitrogen dioxide by taking into consideration several climate and other kinds of environmental data for the city of Los Angeles. Multiple Neural network models were built in order to achieve the optimal prediction results. The final results showed a very good prediction accuracy.
Another research [14] has shown that artificial intelligence can be applied in developing methodologies for predicting air SO2 concentrations in industrial areas with thermal power plants which have highly polluted ambient. This study has focused on air pollution modelling and in SO2 emissions forecasting and the results showed a good prediction accuracy.
In this research, the construction of artificial neural network models is investigated for forecasting key air pollutant factors. In the next sections, the followed methodology and the theoretical background are described, and also the factors that have been examined in order to develop the optimal network topology of the forecasting model and the produced results.

43.2 Theoretical background

43.2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are considered as artificial computational systems that simulate the neural structure of the human brain. The input data traverse through the neural connections.
A neural network elaborates the data from the input parameters. The output results are produced according to the input parameters [15].
Artificial neural networks are used in this study in order to forecast the values of the key air pollution factors: carbon monoxide, ozone, sulfur dioxide, and nitrogen dioxide.
In a feed forward multilayer neural network, the network structure includes neurons, which are connected in a forward only direction. A typical feedforward neural network structure consists of an input layer, one or more hidden layers and an output layer. Every layer consists of a number of neurons [16][17].
A Feed Forward Multilayer Perceptron (FFMLP) was utilized in this research, since many studies have shown that it is the most suitable for issues that have to deal time series predictions. The structure of a typical feed forward neural network is shown in figure 1.

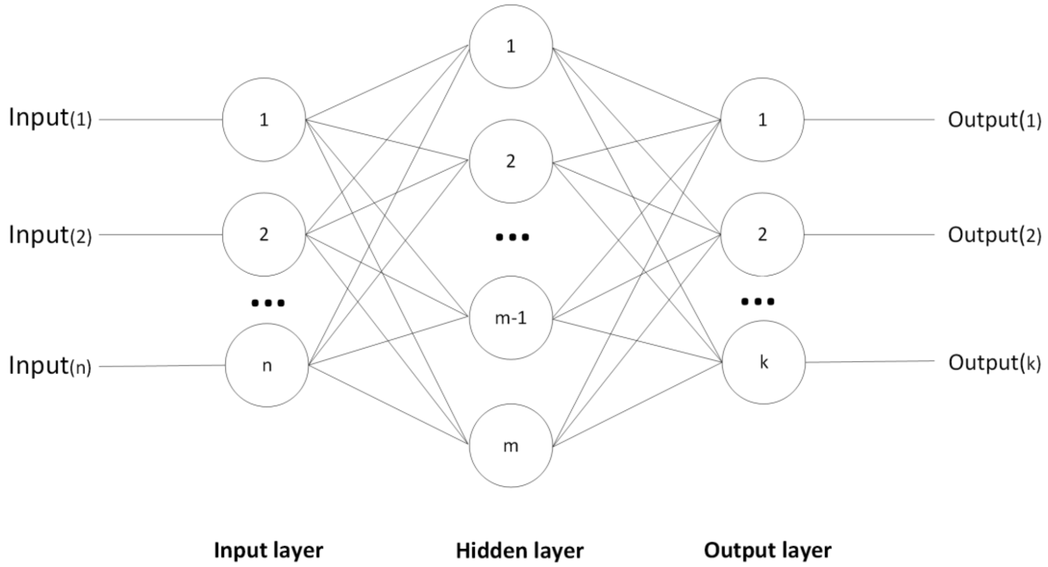

Figure 1: A simplified structure of a typical feedforward neural network. *n* is the number of neurons in the input layer, *m* is the number of neurons in the hidden layer and *m* is the number of neurons in the output layer.

43.2.2 Scaled conjugate gradient algorithm

The Scaled Conjugate Gradient (SCG) algorithm was proposed by Møller in 1993 [18]. The Scaled Conjugate Gradient algorithm was implemented in this research for training the artificial neural network models. Scaled conjugate gradient algorithm is one of the fastest training algorithms among several others training algorithms [18].
Conjugate gradient techniques produce faster convergence than gradient descent methods by applying a search in all the gradient directions in order to determine the step size scaling method. Scaled conjugate gradient algorithm minimizes the goal functions and uses a step size scaling method to achieve a faster learning process [18][19][20].

43.2.3 Key air pollutant factors

The key air pollutant factors in urban environmental that are examined in this research are: carbon monoxide, ozone, sulfur dioxide, and nitrogen dioxide. These factors have a negative impact on human health as many researches have shown [21][22][23]. According to many researches, the prementioned pollutant factors have been associated with various diseases.
According to several researches, mortality is associated with air ozone and nitrogen dioxide levels in several places of the world [21][22]. Also, a research has shown a strong association between air carbon monoxide concentrations and the hospitalizations for heart failure in several Canadian cities [23]. According to another research, proinflammatory mediators were induced by ozone and nitrogen dioxide in human bronchial epithelial cells [24]. Also, another research, showed the association of ozone and daily mortality rate in several cities of East Asia [25]. Furthermore, another research has shown that air pollutant factors: nitrogen dioxide, sulfur dioxide, and carbon monoxide have a negative impact on human health [26].

43.3 Research methodology

The research methodology is divided into four stages: data collection, data preparation, neural network forecasting model construction, the application of the optimum neural network model in order to forecast the values of the air pollutant factors. In the first stage, air pollution data were collected and in the second phase the data were cleansed and prepared for feeding the neural network models. In the third stage, several kinds of neural networks were developed by examining different topologies in order to construct the optimal neural network prediction model. In the last phase, the optimum neural network model was tested in order to predict the concentrations of the air pollution factors.

43.4 Results

43.4.1 Study Area and Data Collection

The data were retrieved from the US Environmental Protection Agency (EPA) for the city of New York. Data regarding the daily concentration of carbon monoxide, ozone, sulfur dioxide, and of the nitrogen dioxide were processed and prepared in order to be used as input in the feed forward neural network models.
The air pollution data were collected, checked for incoherencies and duplicates and then prepared to feed the neural networks. The period of time that was examined was from January 2016 to June 2016 for the city of New York in USA.

43.4.2 Neural Network Models

The artificial neural network models were developed by utilizing several input parameters that affect the levels of the predicted pollution factors: ozone, sulfur dioxide, nitrogen dioxide and carbon monoxide, such as: the maximum temperature, minimum temperature, average temperature, wind speed, humidity, sunlight hours and the historical data of O_3, NO_2, SO_2 and CO [21]. The input values are: the daily max 8-hour ozone concentration (ppm), daily max 8-hour CO concentration (ppm), the daily maximum 1-hour nitrogen dioxide concentration (ppb), the daily maximum 1-hour sulfur dioxide concentration (ppb), sunlight hours, and also the minimum, maximum and average daily temperature. The output values are the predicted data of O3, NO_2, SO_2 and CO.
The data were separated into three different parts. The 70% of the primary data was used as the training set, the 15% for the validation set and the 15% for the test set. The scaled conjugate gradient algorithm was utilized as the learning algorithm. The training data set was used in order to train the artificial neural network with historical data. The validation set was used in order to evaluate the performance of the artificial neural network models.

43.4.3 Optimum neural network model

Several network topologies were examined by testing different network parameters. The optimal neural network topology was evaluated according to the performance of every developed artificial neural network model. Different neural network topologies were tested regarding the number of the hidden layers (one to two), the number of neurons in every

hidden layer (one to forty neurons) and the most common transfer functions of the hidden layers: Linear Transfer Function (LTF), Tanh-Sigmoid Transfer Function (TSTF), Log-Sigmoid Transfer Function (LSTF).
The optimum network topology was the one with one input layer, and one output layer and with two hidden layers. The optimal network topology that was found consists of 18 neurons in the first hidden layer and 25 neurons in the second hidden layer. The transfer function of the first hidden layer was Tanh-Sigmoid Transfer Function (TSTF) and of the second hidden layer the Linear Transfer Function (LTF). The optimum network model was evaluated by examining the observed minimum Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) among all the other tested neural network models. Table 1 illustrates the best neural network models developed by testing different topologies.

ANN MODEL	Number of hidden layers	Number of neurons 1st hidden layer	Number of neurons 2nd hidden layer	Transfer Functions	MSE Validation Error	MSE Training Error	MSE Test Error
1	2	15	17	LSTF – LTF	62.1506	45.4868	96.1720
2	2	18	25	TSTF – LTF	5.1841	1.8054	5.6143
3	2	20	25	TSTF – LTF	78.8190	58.6007	93.6174
4	2	25	30	LSTF – LTF	69.6709	55.6106	82.0046

Table 1: The best neural network models constructed by testing different topologies.

According to table 1, ANN model 2 was the best forecasting model. The Mean Squared Error (MSE) of the optimal model was found to be 5.1841 at epoch 67. The Root Mean Squared Error (RMSE) of the optimal model was found to be 2.2769. Figure 2 shows the topology of the finally constructed optimum artificial neural network model.

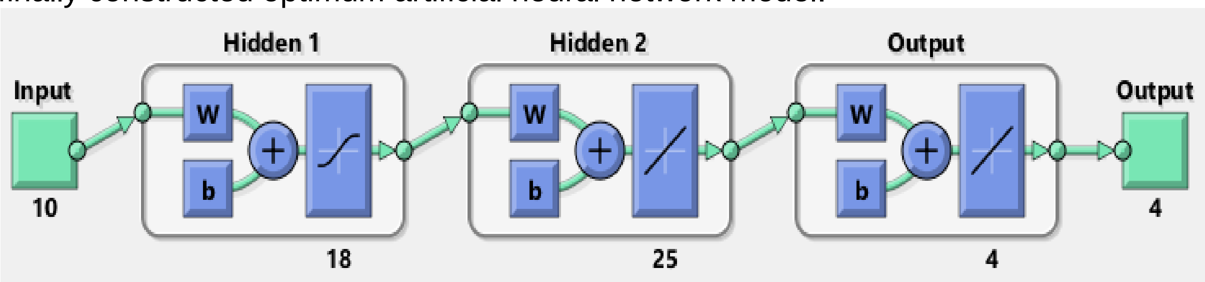

Figure 2: The topology of the optimal artificial neural network model.

The performance plot of the optimal neural network model is illustrated in figure 3 (according to the minimum Mean Squared Error (MSE)). The blue, green and red lines illustrate the performance of the train set, the validation set and the test set correspondingly.

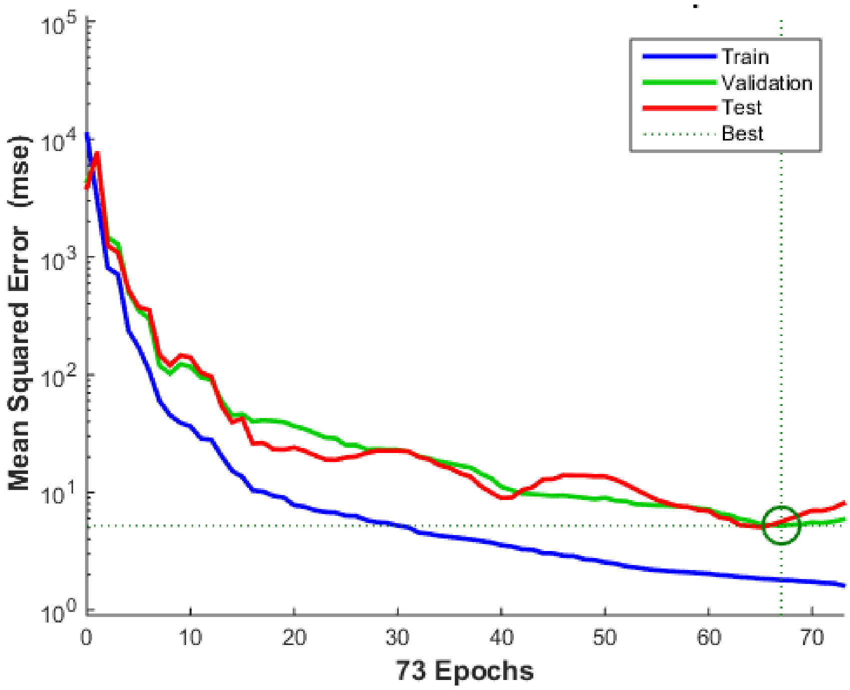

Figure 3: The performance plot of the train set, the validation set and the test set of the optimal neural network model according to the minimum Mean Squared Error (MSE).

43.5 Conclusions and Discussion

Adopting artificial intelligence in forecasting air pollution factors can facilitate the environmental decision making and planning strategies. In this paper, neural network models are developed and compared for their performance in order to discover the optimal model for predicting the levels of the environmental air pollutant factors.
The final results showed an increased accuracy in forecasting the key air pollutant factors that were selected. The optimal artificial neural network model was constructed by taking into consideration multiple factors that affect the concentration of the air pollutant factors, and also by examining several network topologies of the neural network in order to discover the optimum forecasting model. The Multilayer Feedforward Perceptron was utilized in this research since it is the most suitable for time series forecasting according to the literature.
The levels of the key air pollution parameters: carbon monoxide, ozone, sulfur dioxide and nitrogen dioxide were chosen to be predicted, since these factors are related with human health problems and especially with respiratory deceases. This research can contribute to the prevention of these kinds of sequences on human health.
The proposed model can be useful to the authorities in facilitating the adoption of proactive measures so as to improve the effectiveness of environmental management and planning strategies and to be used as a decision-making tool for applying more efficient practices in protecting public health and also in preventing the pollution and the degradation of the natural environment.

43.6 Acknowledgements

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43.7 References

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