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NEURAL NETWORKS BASED MODELLING OF TRAFFIC RELATED AIR POLLUTION

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ABSTRACT

In this study, an artificial neural network modelling has been proposed and employed for modelling of NO_2 pollution on the roadside of Greater London Area. For this purpose, two small programs were written in MATLAB and used for modelling of roadside NO_2 pollution. It was found that the R-value is almost 0.92, and t-test results and P-values were found in the ranges of 0.00-0.30 and 0.5-0.8 for the network outputs, respectively. It was conclude that difference between the means of the measured and predicted values of NO_2 pollution is within the 95.0% confidence level.

Key Words: Artificial Intelligent, Forecasting, Traffic Pollution, NO_2, Roadside.

1. INTRODUCTION

Air pollution is a growing problem because of the increasing urban population causing high density of vehicle traffic, more and more electricity needs, and expanding commercial and industrial activities. The importance of the preventing air pollution has been increasing in recent years, due to increasing knowledge of polluting sources and their pollution levels. NO_2 is one of the environmentally important air pollutants that have been associated with urban air quality problems and mainly released from traffic vehicle exhaust. Nitric oxide (NO) is the primer pollutant from vehicle exhaust and is ultimately converted to NO_2 by reaction with ozone (O_3) in the atmosphere.

The ultimate objective of an air quality management strategy is to achieve acceptable and sustainable air quality for a region. To achieve this aim, prediction and assessment of future air quality is very important. By means of an air pollution model, it is possible to achieve acceptable and sustainable levels of air quality for a region. Precise daily air quality forecast are needed for individual region (i.e., an urban area) when appropriate health advise is to be issued to the public using a health hazard warning system.

An effective local air quality management system that provides authorities with information about current and predicted air quality throughout the area and so enable assessment to be undertaken as to whether pollution levels exceed National Air Quality Standards or are likely to exceed it in the near future. In this regard, air pollution models can be a very effective tool in planning strategies for management of local air quality and can provide a rational basis for the control of air pollution. If properly designed and evaluated, air pollution models play considerable role in any air quality management system.

Classical air quality models can broadly be classified in two groups: physical models and mathematical models, of which can be deterministic or statistical. Deterministic models are based on fundamental mathematical descriptions of atmospheric processes, whereas statistical models are based upon semi-empirical statistical relations among available data and measurements (Zanetti, 1990).

In recent years, Artificial Intelligence (AI) based techniques have been proposed as alternatives to traditional statistical ones in many scientific disciplines. Artificial neural networks (ANN), one of the most popular AI methods, are considered to be simplified mathematical models of brain-like systems. Neural networks are generally trained by means of “training data”, and due their property of generalization, they can learn new associations, new functional dependencies and new patterns.

Artificial neural networks (ANNs) are parallel calculation architectures whose structure is based on the human brain. If suitably ‘trained’ using a set of examples, they can ‘learn’, i.e they can extract the link between the input data and the corresponding output data (Lippmann, 1987). So, ANNs could be used to solve a number of problems of classification and, more generally, black-box identification, in which ‘a priori’ knowledge of the model is not needed (Chen and Billings, 1992). To this we must add the fact that operations are relatively simple and can be performed quite systematically. The learning phase is, in fact, entrusted to special algorithms such as the back-propagation algorithm, which is a simple steepest descent optimization strategy. The term back-propagation refers to the fact that the gradient vector is calculated in the direction opposite to the flow of the output of each node.

Due to these properties, Artificial Neural Networks have been widely used for modeling and forecasting. Especially, the “multilayer perceptron” has been applied within the field of air quality prediction in the last decade. A summarized review of the applications of ANN in the atmospheric sciences has been carried out by Gardner and Dorling (1998). ANN models have been studied by various investigators for SO_2 (Boznar et al., 1993; Chelani et al., 2002; Yildirim et al., 2003), for NO, NO_2 and NOx (Gardner and Dorling, 1999; Perez and Trier, 2001), ozone (Jorquera et al, 1998; Gardner and Dorling, 2000) and PM2.5 (Perez et al., 2000; Perez and Ryes, 2001) concentration forecasting.

This study aims to estimate roadside NO_2 pollution levels depending on meteorological parameters, some air quality data (i.e., O_3 and NO) and total traffic flow by using artificial neural networks (ANN). Its aim is essentially to focus on the usefulness of artificial neural network for the identification of short-term prediction models based on recorded time-series data.

2. MATERIALS AND METHODS

2.1. Artificial Neural Network Models with Backpropagation Algorithm

The backpropagation algorithms (BP) use input vectors and corresponding target vectors to train a neural network (NN). NN with sigmoid layer and a linear output layer are capable of approximating any function with a finite number of discontinuities (Hagan, 1996). Backpropagation algorithms are based on other optimization techniques, such as conjugate gradient and Newton methods. For properly trained backpropagation networks, a new input leads to an output similar to the correct output. This NN property enables to train a network on a representative set of input/target pairs and get good forecasting results.

A two-layer neural network with tangential sigmoid transfer function at hidden layer and a linear transfer function at output layer was used. Due to its highly optimization capability, Levenberg-Marquardt algorithm is used as the backpropagation algorithm. This structure was tested and found as a useful structure for modelling of air pollutants (Karaca et al., 2005). The structure of the neural network used in the study is given in figure 1. This NN has ***k*** input parameters and ***l*** output parameters which are essential for accurate modelling of the air pollution. The input parameters, number of neurons at hidden layer and output layer should be determined according to current data gathered.

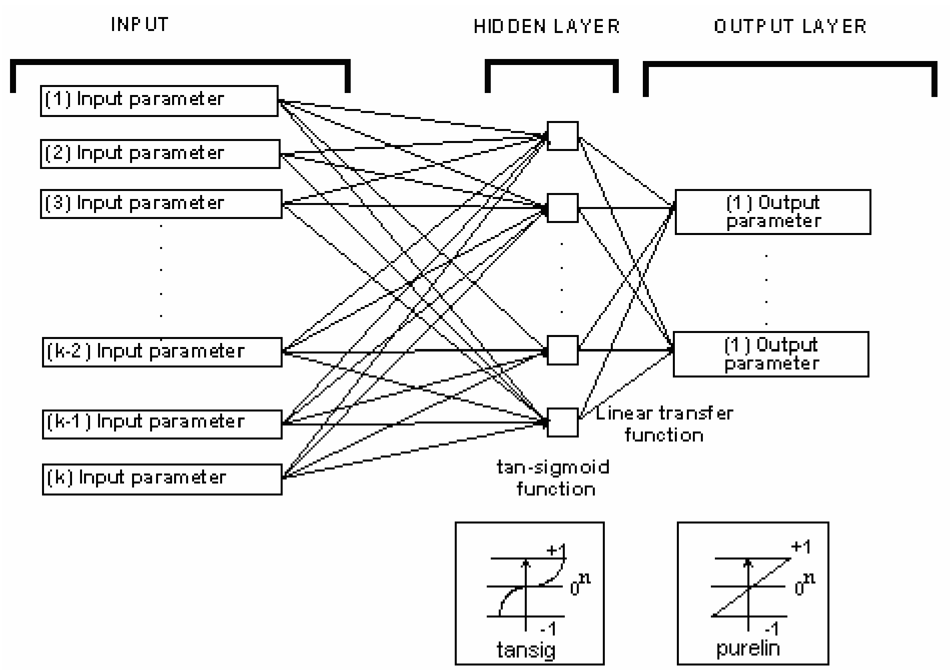

Figure 1. General Structure of a Neural Network.

2.2. Experimental Data

The location of the air quality monitoring station is in Staines site, situated at the edge of the clockwise carriageway of the London orbital motorway, M25 between junctions 13 and 14, to the west of London and the pollutants monitored in 1997. Traffic flows at this site are considerably higher than those at the other locations, with typical daily flows of 175,000 and peak hour flows of between 12,000 and 15,000 vehicles.

The input data includes traffic flow, concentrations of NO, NO_2 and Ozone, and meteorological data. The datasets consist of sequential hourly time series of concentrations and meteorological variables. The time period selected covers year of 1997. All traffic flow, air quality and meteorological data are presented as hourly averaged values.

The relevant traffic flow data was obtained from Highway Agency. This data contains hourly traffic volumes and average driving speed, separately for various vehicle categories (light-duty traffic, busses and other heavy-duty traffic). In this study, hourly total traffic volumes in 1997 were employed for modelling.

The hourly concentrations of NO, NO_2 and Ozone were available for the station of Stainnes during the selected year of 1997. TRL provided air quality and meteorological data from the site for modelling. Hourly meteorological data and air quality data were obtained from the M25 motorway site automatic measuring station. The precipitation (rain) values were obtained from London Weather Centre during 1997.

It is suggested to use TAU as an input parameter instead of wind direction (WD) and wind speed (WS) (Berkovich, 2000). The travel time and the effective travel distance (X) can be calculated as follows:

$$TAU = \frac{X}{u} \quad \text{and} \quad X = \frac{d}{\sin(FI)} \tag{1}$$

Where u is the wind speed and X is effective travel distance, d is the distance from the road (perpendicular) and FI is the angle of the wind with respect to the road axis.

3. RESULTS AND DISCUSSION

3.1. Model Training, Evaluation and Testing

Model building, training and testing are performed using MATLAB compiler. Two small programs were written and used for modelling in MATLAB. The data is divided into two matrix called as P matrix and T matrix. P matrix contains the input parameters of the model and T matrix contains the target of neural network. The values of each parameter were transformed to the interval [0, 1] by using equation (2);

$$V_i' = 1 - \left[\frac{MaxV_i - V_i}{MaxV_i - MinV_i} \right] \quad (2)$$

Where, *Vi* is the transformed ith value of array, $MaxV_i$ is the maximum value of an array, $MinV_i$ is the minimum value of an array, and V_i is the ith value of an array. The input and output parameters used in the models were presented in Table 1.

Table 1. Parameters of NN model

PARAMETERS		DIMENSIONS/RANGES
Input Parameters		
1	TAU (Travel Time)	Second (s)
2	TEMP (Temperature)	°C
3	RH (Relative Humidity)	%
4	SR (Solar Radiation)	W/m^2
5	Rainfall	Mm
6	Traffic Flow	total
7	NO	ppb
8	Ozone	ppb
Output Parameter		
1	NO_2	ppb

The available data [N=6658] was divided into section: training, validation, and test subsets, which are randomly chosen by the model. One fourth of the data [1664] was taken for the validation set, one fourth for the test set [1664] and one half for the training set [3330]. The network should have one output neurons since there is one target.

With the purpose of obtaining of maximum efficiency, which corresponds to a neuron number, neurons of the model in the hidden layer were increased one by one from 1 to 100 neurons and the responses of the model were obtained well known statistical indices: Mean Squared Errors (MSE). It was found that there are several local minimum and maximum of MSE values for the model. The relationship between Neuron numbers and MSE is given in figure 2 indicating high error after 15 neurons. However, generally 10-20 neuron regions can be considered as global minimum region. Due to its low error value, finally it was decided to select 15 neurons as the number of neurons for the optimum structure of the model.

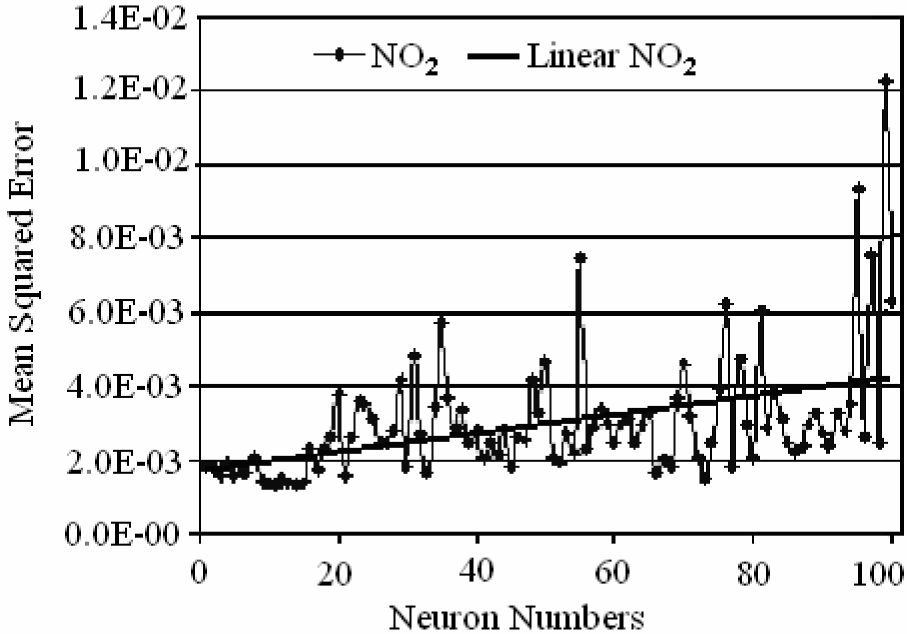

Figure 2. Neuron Numbers vs. Mean Squared Error (MSE) values of network outputs

The training stopped after 97 iterations because validation and test MSE values were reached a steady condition. The training, validation and test errors of the model are given in figure 3. The obtained results are reasonable, since the test set error and the validation set error have similar characteristics, and it doesn't appear that any significant over fitting has occurred.

In order to find performance analysis of the network response, entire data set was put through the network (training, validation and test) and a linear regression was performed between the network outputs and the corresponding targets. All of the outputs seem to track the targets reasonably well, and the R-values are almost 0.92. Performance of the model for NO_2 modelling is represented in figure 4 indicating model results are in good agreement with the measured data set.

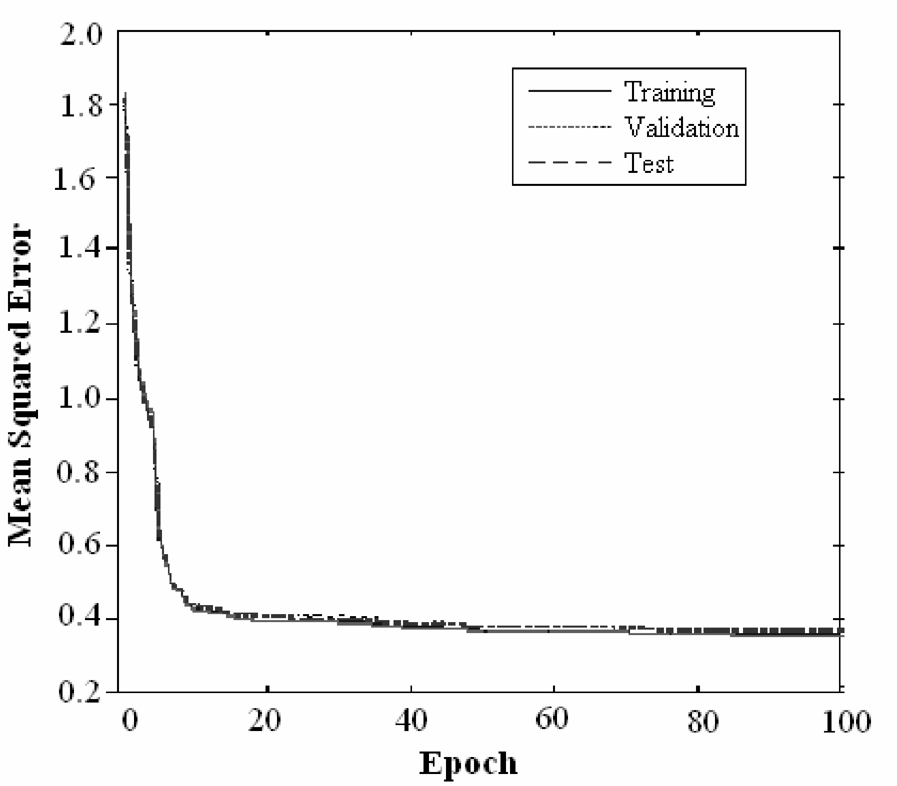

Figure 3. The training, validation and test errors of the training progress.

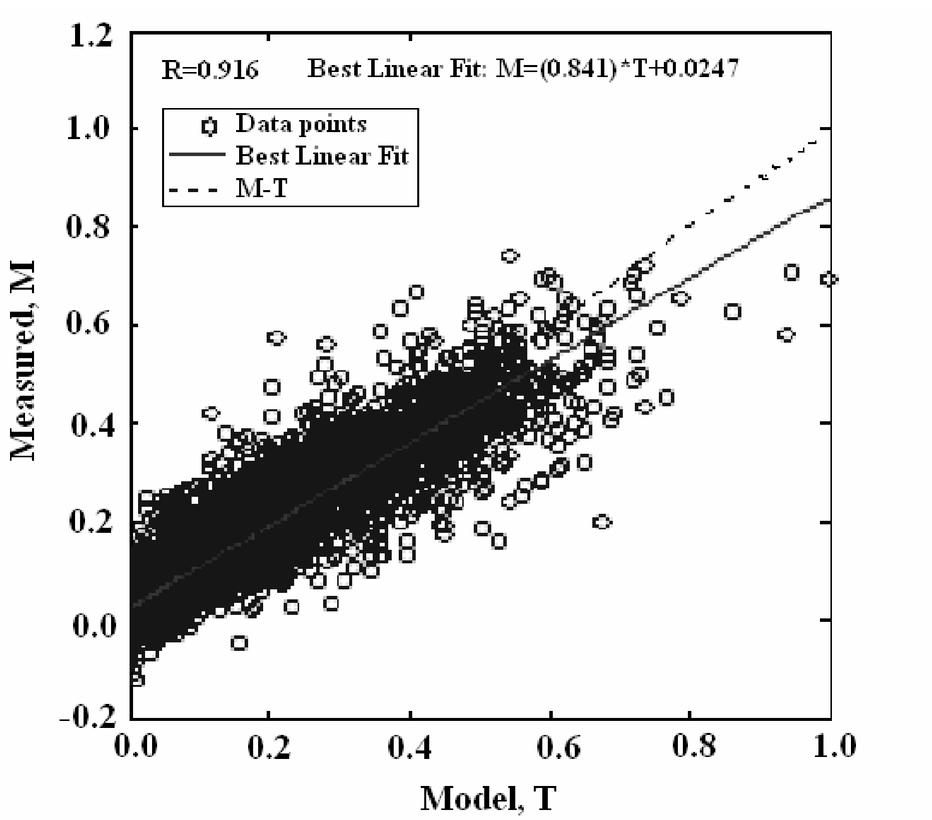

Figure 4. Performance of the model for roadside NO_2 pollution modelling

4. CONCLUSIONS

Entire data set was put the through the network (training, validation and test) and a linear regression was performed between the network outputs and the corresponding targets. All of the outputs seem to track the targets reasonably well, and the R-values are almost 0.92 for NO_2 pollution. The t-test was used to compare the means of the measured and predicted values. T-test results and P-values are found in the ranges 0.00-0.30 and 0.5-0.8 for the network outputs, respectively. Statistically, there is no significant difference between the means of the measured and predicted values of NO_2 pollution at the 95.0% confidence level. They have very good agreements on the trends between forecasted and measured data. It can be concluded that artificial neural networks with backpropagation algorithm are useful neural techniques for the identification of short-term prediction models based on recorded time-series data.

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REFERENCES

Berkowicz, R., 2000. A simple model for urban background pollution. Environmental Monitoring and Assessment 65, 259–267.

Boznar, M., Lesjack, M and Mlakar, P. (1993) A Neural Network Based Method for Short-term Predictions of Ambient SO_2 Concentrations in Highly Polluted Industrial Areas of Complex Terrain, Atmospheric Environment, vol.270-B, no:2, 221-230.

Chelani, A.B., Rao, C.V.C., Phadke, K.M. and Hasan, M.Z. (2002). Prediction of sulphur dioxide concentration using artificial neural networks, Environmental Modelling & Software 17, 161–168.

Chen, S., Billings, S.A., 1992. Neural networks for nonlinear dynamic system modelling and identification. Int. J. Control 56 (2), 319–346.

Gardner, M.W. and Dorling, S.R. (1998) Artificial Neural Network (The Multi Layer Perception) - A Review of Applications in the Atmospheric Sciences, Atmospheric Environment, 32, 2657-2636.

Gardner, M.W. and Dorling, S.R., 1999. Neural Network Modeling and Prediction of Hourly NOx and NO2 Concentration in Urban Air in London, Atmospheric Environment, 33, pp.709-719.

Gardner, M.W. and Dorling, S.R., 2000. Statistical Surface Ozone Models: An Improved Methodology to Account for Non-linear Behavior, Atmospheric Environment, 34, pp.21-34.

Hagan, M. T., Demuth, H. B., and Beale, M. H., “Neural Network Design”, Boston, MA: PWS Publishing, 1996.

Jorquera, H., Perez, R., Cipriano, A., Espejo, A., Letelier, M.V and Acuna, G., 1998. Forecasting Ozone Daily Maximum Levels at Santiago, Chile, Atmospheric Environment, 32, pp.3415-3424.

Karaca, F., Alagha, O., Ertürk, F., “Application of inductive learning: air pollution forecast in Istanbul, Turkey”, Intelligent Automation and Soft Computing, Vol. 11, No. X, pp. 1-10 (in press), 2005-b.
Lippmann, R.P., 1987. An introduction to computing with neural nets. IEEE ASSP Mag 4 (2), 4–22.
Perez, P and Ryes, J. (2001) Prediction of particulate air pollution using neural techniques, Neural Computing and Applications, 10, 165-171.
Perez, P and Trier, A. (2001). Prediction of NO and NO_2 concentrations near a street with heavy traffic in Santiago, Chile, Atmospheric Environment 35, 1783-1789.
Perez, P., Trier, A., Reyes, J., 2000. Prediction of PM2.5 concentrations several hours in advance using neural networks in Santiago, Chile, Atmospheric Environment, 34, 1189-1196.
Zannetti, P., 1990. Air Pollution Modeling (Theories, Computational Methods and Available Software). Van Nostrand Reinhold, New York.
Yildirim, Y., Bayramoglu, M and Hasiloglu, S. (2003). Prediction of sulfur dioxide daily levels in the city of Zonguldak using an adaptive neuro-fuzzy based method, 12(10), 425-432.