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Forecasting Extreme PM_{10} Concentrations Using Artificial Neural Networks

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ABSTRACT: Life style and life expectancy of inhabitants have been affected by the increase of particulate matter 10 micrometers or less in diameter (PM_{10}) in cities and this is why maximum PM_{10} concentrations have received extensive attention. An early notice system for PM_{10} concentrations necessitates an accurate forecasting of the pollutant. In the current study an Artificial Neural Network was used to estimate maximum PM_{10} concentrations 24-h ahead in Tehran. Meteorological and gaseous pollutants from different air quality monitoring stations and meteorological sites were input into the model. Feed-forward back propagation neural network was applied with the hyperbolic tangent sigmoid activation function and the Levenberg–Marquardt optimization method. Results revealed that forecasting PM_{10} in all sites appeared to be promising with an index of agreement of up to 0.83. It was also demonstrated that Artificial Neural Networks can prioritize and rank the performance of individual monitoring sites in the air quality monitoring network.

Key words: Air pollution, Polluant concentration, Urban pollution, Artificial Neural Network

INTRODUCTION

A major factor in public health refers to air quality which depends primarily on particulate matters (Puza *et al.,* 2011; Shad *et al.,* 2009;Sivagangabalan *et al.,* 2011; Chiou *et al.,* 2009; Goswami, 2009; Ahmad *et al.,* 2009). The direct relation of particulate matter with diameter less than 10 mm (PM_{10}) and health effects(Montero Lorenzo *et al.,* 2010; Halek *et al.,* 2010; Yi *et al.,* 2011) has been well recognized. Life style, life expectancy and mortality have been affected by an increase of PM_{10}. For instance results of a study have shown that an increase of PM_{10} concentration can lead to the increase of the rate of mortality in the following day (Hooyberghs *et al.,* 2005). Moreover, these species can destroy goods and reduce horizontal visibility in the built environments.

Air Quality MonitoringNetworks (AQMN) are designed to observe air pollution levels during the time(Motesaddi Zarandi *et al.,* 2008; Kim *et al.,* 2010). The design of such networks has been traditionally based on an ad-hoc fashion by installing pollutant sensors in hot-spots. However, there have been several attempts to design most effective monitoring networks by firstly considering relevant parameters such as population density and pollution variability (Kanaroglou *et al.,* 2005) and then most recently assigning less sensors while capturing maximum variance (Nejadkoorki *et al.,* Sivagangabalan *et al.,* 2011) in the AQMN. Once such networks launched, there might been frequent missing data due to the malfunction or failure operations especially when a long term monitoring is scoped.

Furthermore, air pollution has been a major concern in Tehran for recent years and the city has been suffering from PM_{10}.The authorities have defined annual and daily restriction for this pollutant. The city's major source of PM_{10} is road traffic especially vehicle species with the poor standards (e.g. old buses).

Artificial Neural Networks (ANNs) with the development of computer sciences have provided a powerful platform for different fields including air pollution modelling. Compared to the classical statistics these can cop of with the sophisticated non-linear functions in high-dimensional spaces. ANNs is inspired and motivated by the structure and functional characteristics of human neurons and biological neural networks. Animal and human nervous systems consist of millions of interconnected cells which is called neuron. Each neuron is a complex arrangement which deals with incoming signals in various ways. Similarly, ANNs consists of an interrelated set of artificial

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neurons, and it processes information using a connectionist approach to computation. ANNs are computing systems which can be trained to learn a complex relationship between two or more variables or data sets (Mohebbi and Baroutian, 2008; Rajasimman *et al.,* 2009). Basically, they are parallel computing systems composed of interconnecting simple processing nodes (Lau, 1992).Neural networks utilize a matrix programming environment making most networks mathematically challenging. Among the available artificial neural networks, the feed-forward neural network is one of the most important historical developments in neurocomputing. The feed-forward neural network is a nonlinear function of its inputs which is the composition of the functions of its neurons. There have been successful studies in air pollution modelling for forecasting pollutants O_3, SO_2, CO and most recently PM_{10} using ANNs. Several studies have been implemented to forecast PM_{10} in Chile, Belgium, Finland, Greece, and the USA (Grivas *et al.,* 2008; Hooybergh*s et al.,* 2005; Ibarra-Berastegi *et al.,* 2008; Karatzas and Kaltsatos, 2007; Konovalov *et al.,* 2009; Kukkonen *et al.,* 2003; Rimetz-Planchon *et al.,* 2008). In the case of PM_{10}, one main concern is to predict maximum concentrations on the following day. This is vital as commuters can manage their destinations or postpone their journeys when an extreme concentration of PM_{10} is expected. There have been few attempts to forecast extremes concentration of PM_{10} for the next day (Brunelli *et al.,* 2007; Perez and Reyes, 2002). Perez and Reyes (2002) developed an integrated artificial neural network model to forecast the maximum of 24 h average of PM_{10}concentrations and applied it to the case of five monitoring stations in the city of Santiago, Chile. Inputs to their ANNs model werePM_{10}concentrations measured at the five stations plus measured and forecast values of meteorological variables. Grivas and Chaloulakou (2006) evaluated the potential of various developed neural network models to provide reliable predictions of PM_{10} concentrations in the Greater Athens Area. The model inputs included PM_{10}concentrations from4 measurement locations and meteorological variables.In another work, Papanastasiou et al. (2007) developed a model based on the neural network to produce predictions of daily average value of PM_{10} concentration in the urban area of Volos, a medium-sized coastal city in central Greece. The model utilized the variables as inputs, which incorporated meteorology and annual variation of PM_{10} concentration.

Tehran, the capital of Iran has a population of about 8.5 millions and been surrounded by mountains in the North and East with no close river or sea. The city's air pollution problem is well known (Ashrafi *et al.,* 2009; Monavari and Mirsaeed, 2007)and the latest studies have revealed that the levels of PM_{10} are significant (Halek *et al.,* 2010)and greater than the standard level of 50 µg m^{-3}. An official AQMN has been effectively launched since earlier 2000s, though there has been lack of full data due to technical problems for some of its sites. The location of eight stations measuring several pollutants including PM_{10} can be seen in Fig. 1. Exploring the dataset revealed that there are missing data for a pollutant or several pollutants that may have not been measured by sensors. Therefore it is crucial to discover sites that have the most representative performance in the AQMN in the case of any operational failure. A description of monitoring data has been given in Table 1.

This paper initially aimed at predicting maximum PM_{10} concentrations for the next day using the pollutants and meteorological parameters of the day before. The dataset were varied for different stations for 2001-2009. Furthermore, a number of parameters studied previously (Cai *et al.,* 2009; Corani, 2005; Giri *et al.,* 2008; Hooybergh*s et al.,* 2005; Viotti *et al.,* 2002) or were thought to have an impact on the maximum PM10 concentration of the next day were considered. These were date, day of week (1-7), month of the year (1-12), mean of solar radiation (KW m^{-2}), mean and max of temperature (º C), mean wind direction (º) and speed (m s^{-1}), mean NO, mean CO, and mean and max of PM_{10} of the day before and mean solar radiation (KW m^{-2}), mean temperature (º C), mean wind direction(º), and mean of wind speed (m s^{-1}) of the next day. In practice hourly data slots were first extrapolated to daily slots. A filter was then applied to exclude those days with missing data for pollutants or meteorological parameters. This was carried out as we thought this might lead to error, though there might be some techniques to estimate missing data nowadays. Consequently discrete matrices containing pollutants and their corresponding meteorological values were built for each site in the AQMN.

MATERIALS & METHODS

We propose an approach based on integrating spatial distribution and ANN to find the most representative sites which their established ANN can be applied for the rest of monitoring network in an AQMN. An ANN is first established for each site in a way which PM_{10} is forecasted with the best accuracy. The developed ANN is then run for the rest of sites and their modelling is then assessed using statistical descriptors. The most common ANNs used in air quality modelling is the Multiple Layer Perception (MLP) network. This network has typically three layers, input layer, hidden layer and target layer. Input layer

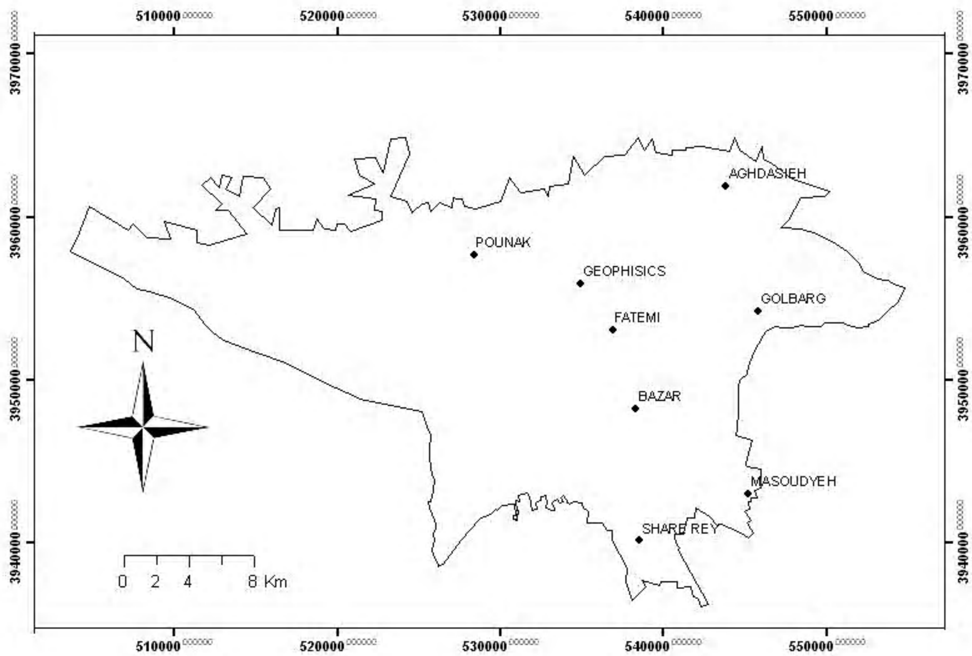

Fig. 1. Location of PM_{10} monitoring stations in the metropolitan area of Tehran, Iran

Table 1. Background description of PM_{10} monitoring in the study area

Representative site	Monitoring period	Entire duration (day)	Missing data (day)	Duration (day)	Mean ± SD	Max PM_{10} (µg/m)
Aghdasieh	2001-2009	2438	1569	869	155±114	986
Bazar	2002-2009	2505	2109	396	249±142	967
Fatemi	2001-2008	2272	1558	714	158±85	840
Geophysics	2006-2009	983	475	508	115±98	983
Golbarg	2008-2009	480	388	92	115±71	506
Masoudieh	2008-2009	457	293	164	179±159	996
Ostandary	2009-2009	155	116	39	208±167	883
Poonak	2007-2009	761	351	410	116±90	998
Shahrerey	2006-2009	1297	618	679	101±77	1000

consists of nodes (e.g. meteorological parameters) which are relevant variables expected to predict air pollutant concentrations. Each node in the input is then connected to all nodes of the following layer which is either a hidden or a target layer. A signal in every node of the following layer is then shaped which is a function of linear integration of the incoming inputs. The function is known activation function and is mainly sigmoid as:

$$f(X) = \frac{1}{1+e^{-X}} \quad (1)$$

The generated signal is then sent to every node in the next layer. Signals are then reached the target to produce new targets known as outputs. Given a difference between target and output new weights are then sent to transfer functions to calculate new outputs till there were new outputs close to targets. The MLP models have been widely applied in forecasting air pollution concentrations because of their strength in capturing non-linear relationship between variables (Karatzas and Kaltsatos, 2007). A typical MLP network is presented in Fig. 2. The intention here is to design an ANN to predict maximum PM_{10} on the following day based on pollutants and meteorological parameters of the day before at each monitoring site. The dataset used here covers 2001-2009. The raw data were in hourly slots for pollutants and meteorological parameters. Therefore a pre-processing stage was required to edit the initial data and create a consistent database having all desired parameters for individual days. This was implemented in MATLAB programming by indexing date and consolidating their corresponding values. If a variable was missing for a particular day, the entire row for that they were excluded, though it would have been possible to estimate parameters. This was because of errors might come when estimating missing values.

The model parameters were then set to an input layer of 19 neurons, an output layer of one neuron and one hidden layer of four to ten neurons. A feed-forward back propagation network with 10 neurons in the hidden layer is shown in Fig. 3.The dataset was divided into training (60%), validation (20%), and test sets (20%) randomly. Feed-forward back propagation neural networks and hyperbolic tangent sigmoid function were then used during the training of networks, setting the maximum of epochs at 1000 and applying an early stopping criterion in order to avoid over fitting.

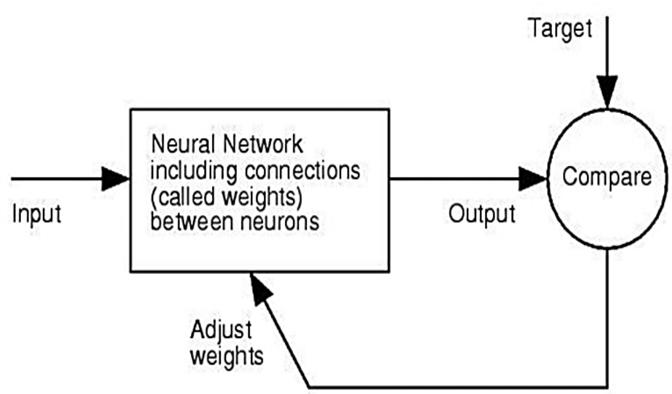

Fig. 2. A typical MLP structure

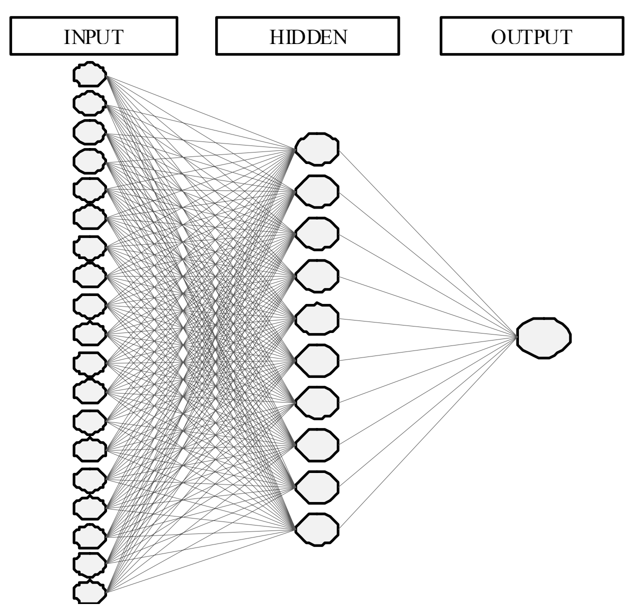

Fig. 3. Feed-forward back-propagation network with three layers and 10 neurons in the hidden layer

The Levenberg–Marquardt optimization was applied for training weights and bias values. The neural networks were implemented; each had 5 runs with MATLAB neural network toolbox. The ANN network topology for individual sites is given in Table 2.

Table 2. ANN topology for individual sites

Representative site	Network topology (nodes per layer)
Aghdasieh	19-6-1
Bazar	19-6-1
Fatemi	19-10-1
Geophysics	19-9-1
Golbarg	19-10-1
Masoudieh	19-6-1
Poonak	19-7-1
Shahrerey	19-4-1

The developed networks for individual sites were then run for the rest of monitoring sites. Furthermore, the ANN that created at each site assumed to be appropriate for other sites and was assigned to forecast PM_{10} for new dataset. The new dataset was completely different both spatially and temporally. For instance an ANN of 19-5-1 of Golbarg station with only 2008 and 2009 data was utilized to forecast PM_{10} for Aghdasieh station within a distance of 8 km for 2001-2009.Finally several statistical descriptors recommended by (Hanna and Baja, 2009) were calculated and their values compared to assess the potential of individual sites to know the extent to which they can cover the monitoring in the study area. These are Index of Agreement (IA) showing the overall accuracy of the model, Fractional Bias (FB) measuring tendency of the model to over predict or under predict, Fraction of predictions within a factor of 2 of observations (FAC2) assessing the model scatter, Normalized Mean Square Error (NMSE) showing the overall accuracy of the model, Geometric Variance (VG) indicating systematic and random errors, Geometric Mean Bias (MG) identifying systematic errors and Correlation Coefficient (r) describing association between observed concentrations and model results.

$$\mathrm{IA} = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \qquad (2)$$

$$FB = \frac{\overline{C_o} - \overline{C_p}}{0.5(\overline{C_o} + \overline{C_p})} \qquad (3)$$

FAC2= fraction of data that satisfy

$$0 \leq \frac{C_p}{C_o} \leq 2.05 \qquad (4)$$

$$NMSE = \frac{\overline{(C_o - C_p)^2}}{\overline{C_o}\,\overline{C_p}} \qquad (5)$$

$$MG = \exp\left(\overline{\ln C_o} - \overline{\ln C_p}\right) \qquad (6)$$

$$VG = \exp\left[\overline{(\ln C_o - \ln C_p)^2}\right] \qquad (7)$$

$$r = \frac{\overline{(C_o - \overline{C_o})(C_p - \overline{C_p})}}{\sigma C_p \sigma C_o} \qquad (8)$$

Where: C_p or P_i are model predictions; C_o or O_i are observations; $\bar{C}$ and σ are the average and standard deviation of the entire dataset respectively.

RESULTS & DISCUSSION

Statistical descriptors (Table 3) reveal that the selected inputs appeared to have a significant contribution to forecast PM_{10} one day in advance. The overall agreement between modelled and observed values for individual sites varied (IA=0.55-0.83 and *r*=0.05-0.73). A peak agreement achieved for Aghdasieh and Bazar stations while Poonak station has the lowest agreement. The *r* values increased significantly from 0.41 for Poonak station to 0.72 towards the Aghdasieh and Bazar stations. The model bias appeared to be relatively low overestimation for Fatemi and Aghdasieh stations. Similarly the lowest scatter was found for these two stations.

The statistical results of developing neural networks and their mean agreement for the rest of sites are summarized in Table 4. It was found that the most representative site is Aghdasieh with an index of agreement of 0.57 and FB of 0.09. We also found that the second representative site is Masoudieh with an IA of 0.48 and FB of -0.149. The Golbarg station was the least representative site (r=0.05 and IA=0.29). Model performance against observations for the best monitoring site, Aghdasieh is illustrated in fig. 4. The developed neural network predicts satisfactory the PM_{10} peaks which are supported by the mentioned statistical predictors(Grivas and Chaloulakou, 2006).

Although the monitored time series seems to be diverse, it has appeared that the ANN with a 4-10 hidden

Table 3. Statistical assessment of the potential of monitoring sites for PM_{10} forecasting

Representative site	IA (1)	FB (0)	FAC2 (1)	NMSE (0)	MG (1)	VG (1)	r (1)
Aghdasieh	0.83	0.02	0.92	0.27	0.96	1.00	0.72
Bazar	0.83	-0.06	0.89	0.15	0.88	1.02	0.73
Fatemi	0.68	0.01	0.94	0.19	0.94	1.00	0.59
Geophysics	0.67	-0.06	0.89	0.49	0.88	1.02	0.55
Golbarg	0.38	-0.30	0.45	0.96	0.82	0.95	0.05
Masoudieh	0.78	0.09	0.71	0.77	1.18	1.02	0.64
Poonak	0.55	-0.08	0.84	0.47	0.84	1.03	0.41
Shahrerey	0.63	-0.06	0.90	0.41	0.89	1.01	0.51
Figure in brackets are ideal values							

Table 4. Average statistical predictors for each monitoring site

Representative site	IA (1)	FB (0)	FAC2 (1)	NMSE (0)	MG (1)	VG (1)	r (1)
Aghdasieh	0.57	0.09	0.82	0.55	1.10	1.06	0.42
Bazar	0.43	-0.21	0.54	0.86	0.91	1.07	0.20
Fatemi	0.37	-0.25	0.65	0.61	0.71	1.34	0.18
Geophysics	0.34	0.19	0.34	-6.43	0.70	0.50	0.26
Golbarg	0.29	-0.70	0.35	1.30	0.48	2.54	0.05
Masoudieh	0.48	-0.14	0.71	0.50	0.82	1.14	0.30
Ostandary	0.33	2.23	0.19	0.07	-0.11	-0.62	0.05
Poonak	0.32	-0.03	0.61	3.26	1.33	1.18	0.20
Shahrerey	0.33	0.04	0.80	1.34	1.04	1.06	0.22
Figure in brackets are ideal values							

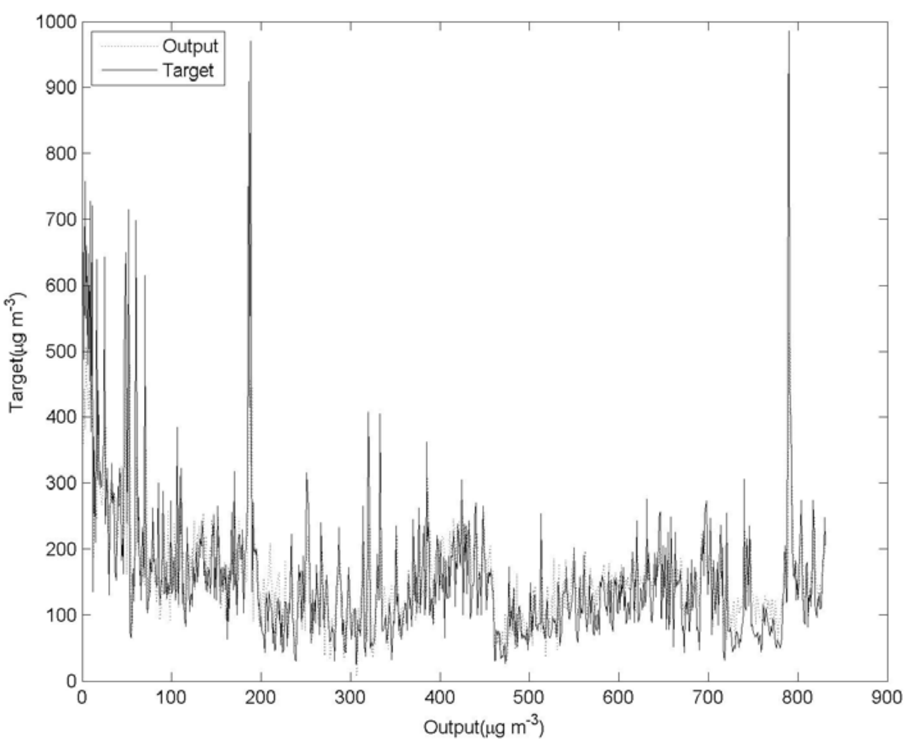

Fig. 4. PM_{10} concentration predicted by ANN (output) in comparison with the observations (target)

layer based on the standard back propagation algorithm, using the simple sigmoid as activation function, resulted as a very effective model to forecast PM_{10} maximum concentrations in the urban area. Results appeared to be in line with findings of similar studies such as (Grivas and Chaloulakou, 2006; Viotti *et al.,* 2002). The input and target variables were normalized scaling (0.1-0.9) presented to the network, as used largely for standard back propagation. While most of the studies have focused on meteorological parameters our results demonstrated that other pollutants have also an important impact on forecasting extreme PM_{10}. The other significance of this research is that based on developed ANNs, it is possible to examine the extent to which the individual sites can cover over the entire AQMN. This approach in particular supports urban air quality monitoring plans to find the most representative monitoring sites or redistributing the current AQMN.

CONCLUSION

A neural network based model was proposed to predict the daily averaged PM_{10} concentrations in the metropolitan area of Tehran. The approach is to define an alarm system for spatial and temporal pollution information to provide choice for commuters to reduce their unnecessary trips in contaminated areas across the city. While most of researches have focused on using meteorological variables this work has considered gaseous pollutants as well to predict maximum PM_{10} one day before. Results showed that the aforementioned variables significantly predicted PM_{10} concentrations. Another conclusion is that the developed NNs for each monitoring site in an air quality monitoring network could offset any missing data in their neighbouring monitoring sites to a certain extent. This provides air quality managers and researchers to rank and prioritize the performance of air quality monitoring sites. The significance of such technique is that it can use data from different time scales.

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