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Dust Level Forecasting and its Interaction with Gaseous Pollutants Using Artificial Neural Network: A Case Study for Kermanshah, Iran

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Abstract: An artificial neural network (ANN) was used to forecast natural airborne dust as well as five gaseous air pollutants concentration by using a combination of daily mean meteorological measurements and dust storm occurrence at a regulatory monitoring site in Kermanshah, Iran for the period of 2007-2011. We used local meteorological measurementsand air quality data collected from three previous days as independent variables and the daily pollutants records as the dependent variables (response). Neural networks could be used to develop rapid air quality warning systems based on a network of automated monitoring stations. Robustness of constructed ANN acknowledged and the effects of variation of input parameters were investigated. As a result, dust had a decreasing impact on the gaseous pollutants level. The prediction tests showed that the ANN models used in this study have the high potential of forecasting dust storm occurrence in the region studied by using conventional meteorological variables.

Key words: Artificial neural network · Dust · Gaseous pollutants · Forecasting model

INTRODUCTION

Recent frequent occurrence of airborne ambient particulate matter inthe west of Iran has generated considerable public and academic interests and become a well-recognized problem in environmental sciences. The occurrence of dusty weather events is influenced by geological and climatic variations as well as human activities. The main sources of these dust storms are arid deserts of neighbor countries such as Iraq and Kuwait. In the time of dry climate condition, strong winds prevail in these areas, lifting large quantities of dust particles into the atmosphere and generating dust storms. Then these fine particulates can be transferred to Iran with a little reduction in concentration. These events lead to reduction of visibility, the deposition pof trace elements and the direct impact on human health via inhalation and require drastic measures such as the closing of the schools and factories and the restriction of vehicular traffic. The forecasting of such phenomena with up to two days in advance would allow taking more efficient countermeasures to safeguard citizens' health and even premature deaths among sensitive groups such as asthmatics and elderly people[1, 2].Over the past years, the health impact of airborne particulate matter (PM) has become a very topical subject. In the environmental sciences a lot of research effort goes towards the understanding of the PM phenomenon and the ability to forecast ambient PM concentrations[3]. A wide variety of operational warning systems based on empirical, causal, statistical and hybrid models have been developed in order to start preventive action before and during episodes [4].

Deterministic photochemical air quality models are commonly used for regulatory management and planning of urban air sheds. These models are complex, computer

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intensive and hence are prohibitively expensive for routine air quality predictions. Stochastic methods are becoming increasingly popular as an alternative, which relegate decision making to artificial intelligence based on neural networks (NN) that are made of artificial neurons or 'nodes' capable of 'learning through training' via historic data [5]. Recently, several researchers started to check the capability of artificial neural network techniques to forecast airborne particulate matter concentrations. They conclude that a NN can be a useful tool to predict PM, although the accuracy they could reach is limited [6-8].

Niskaand coworkers [9] described evolving the neural network model for forecasting air pollution time series. They used a parallel genetic algorithm (GA) for selecting the inputs and designing the high-level architecture of a multi-layer perceptron model for forecasting hourly concentrations of nitrogen dioxide at a busy urban traffic station in Helsinki. Although their models were acceptable in low dust concentration, in all the cases, maximum fitness values of evaluated models were in of order 0.11.

A neural network forecast for daily average particulate matter concentrations in Belgium is developed by Jef and his co-workers [3]. The most important input variable found was the boundary layer height. The model based on this parameter serves to monitor the daily average threshold of 100 ìg/m³. Entering the other input parameters into the model increased the model accuracy [3]. Also, application of artificial neural networks to the prediction of dust storms in Northwest China, using a combination of daily mean meteorological measurements and dust storm occurrence was investigated [10]. The prediction tests showed that the ANN model used in this study has the potential of forecasting dust storm occurrence in Northwest of China by using conventional meteorological variables [10].

A neural network was used to predict particulate matter concentration at a regulatory monitoring site in Phoenix, Arizona. Its development, efficacy as a predictive tool and performance vis-à-vis a commonly used regulatory photochemical model are described by Fernando and his co-wrokers [5]. It was concluded that Neural Networks are much easier, quicker and economical to implement without compromising the accuracy of predictions. Neural Networks can be used to develop rapid air quality warning systems based on a network of automated monitoring stations.

In this study, relationship betweenthe local meteorological measurementsand air quality data collected from three previous days as independent variablesandthe daily pollutants records as the dependent variables was modeled by ANN approach. Filtering and the principle component analysis (PCA) methods are used to refine and reduce the data and number of input variables for introducing to the ANN model. Robustness of constructed ANN investigates and the effects of variation of input parameters are explored. Dust interaction on the other gaseous pollutants was also investigated.

MATERIALS AND METHODS

Artificial Neural Network (ANN): Artificial neural network (ANN) is a group of uncomplicated processing elements arranged in parallel layers, which are internally connected. Artificial neural networks are composed of simple elements operating in parallel layers which are internally connected. The singularity of ANN comes from its capability to be trained and generate interrelationships between observed input and output data without impracticalassumptions. ANN's architecture, activation or transfer function and training algorithm can group into different categories [11, 12]. The selection of the network architecture depends on task to be done specifying the neuron characteristics, network topology and learning algorithm [13]. The multi-layer feed forward back propagation is the simplest feed-forward network. In a standard architecture, neurons are grouped into different layers such as input, output and hidden layers. Fig. 1 shows a simple multilayer perceptron (MLP) model with input layer, one hidden layer containing three hidden neurons and one output layer. Another important factor in ANN design is the type of the transfer functions [14, 15]. A transfer function produces scalar neuron output according to weight, bias and neurons input. Hagen and Demuth [16]reported several transfer functions. The 'S' shape log-sigmoid transfer function as:

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

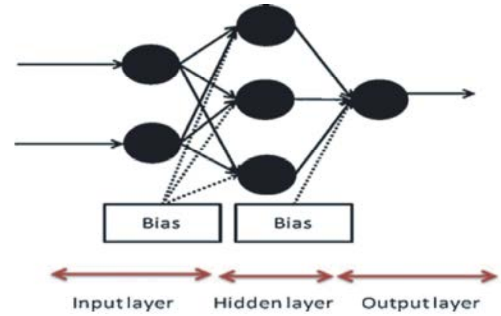

Fig 1: MLP with one hidden layer

is commonly used in multilayer networks that are trained using the back propagation algorithm. Algorithm training is a procedure determining the weights and biases of a network [16]. Such function which its derivatives could be expressed in term of a function may save training time because there is no need to repeat estimation of the derivatives [16].

Training algorithm is a procedure for determining the weights and biases of a network [16]. Due to the convergence speed and the performance of network, the Levenberg-Marquardt training method may be selected as a proper training algorithm. This is preferred compared to the other training techniques such as resilient back propagation, scaled conjugate gradient, variable learning rate back propagation and BFGS quasi-Newton. This is in agreement with the literature [17].

Data Collection: The data used in this study are the meteorological measurements and six air quality parameters collected from 2007 to 2011 in Kermanshah, Iran. Temperature (average, minimum and maximum), pressure, rain precipitation, sunny hours, snowing days, cloudiness value (at 6:30', 12:30' and 18:30'), relative humidity (at 6:30',12:30' and 18:30'), wind speed and direction were used as independent variables. Air quality data collected from three previous days including O_3, NO_2, NO_x, Dust, SO_2 and CO were also used as dependent variables and input for ANN. However, concentrations of O_3, NO_2, NO_x, Dust, SO_2 and CO on the fourth day were selected to be forecasted. Finally, 48 input vectors were prepared to introduce to ANN.

Modeling: To avoid the numerical overflow due to very large or very small weights, input data were normalized according to the following equation:

$$y = \frac{X - X_{mean}}{X_{std}} \tag{2}$$

where X_{mean} is mean value for each row of X and X_{std} is standard deviation for each row of X. The generated data via simulation were changed into the real values and were compared with the experimental results. In pollution prediction, the dimension of the input vectors is large due to high number of parameters affecting the pollution process. For the current case, a technique such as principle component analysis (PCA) is required to reduce the variables. In PCA redundancy in the initial number of variables is reduced and variables with the highest variance are grouped into the main components [18].

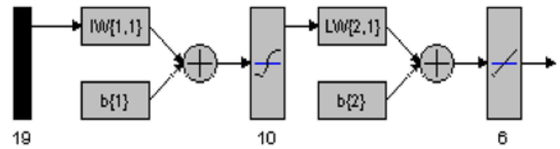

Fig 2: The structure of designed ANN

The preprocessing including filtering, normalization and PCA stages were performed before modeling which lead to the reduction of the number of variables to 19.

The schematic of system structure is depicted in Fig. 2. Filtering process used a moving average filter which the spanfor the moving average was 5. The main idea behind PCA is to derive a linear function consisting of several elements, for each of the vector variables. The variance of the linear function is maximized. The rows in PCA with contribution to total variation less than maximum fraction of variance are removed. Here maximum fraction of variance was considered 0.001.The input vector was used for ANNs to find an appropriate MLP architecture for predicting concentrations of O_3, NO_2, NO_x, Dust, SO_2 and CO on the fourth day. Model's performance can be evaluated through different criteria. In this study root mean square error and R-square were selected for evaluation purposes. The root mean square error, RMSE, was calculated by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - t_i)^2} \tag{3}$$

where t_i is the real value from the field measurements, a_i is the predicted value by model and N is the number of data points. The R-square ranges from 0 to 1. A value closer to 1 indicates high model precision, i.e. a greater proportion of variance is accounted for by the model.

Through a trial- and error method, MLP neural network with one hidden layer were employed as the optimal network structure. The hidden layer consists of 10 neurons. They were used to transform the input data into the desired responses (concentrations of pollutants on the fourth day). With the aid of the hidden layer, any input-output map may be virtually approximated. The well-trained neural network can be used for prediction. Experimental data were divided into three sets for developing model in a random way, 1024 data (60%) for training, 340 data (20%) for validation and 340 data (20%) for querying. The training data were applied for learning process and the validation data were used for checking the over fitting, whereas the querying data were

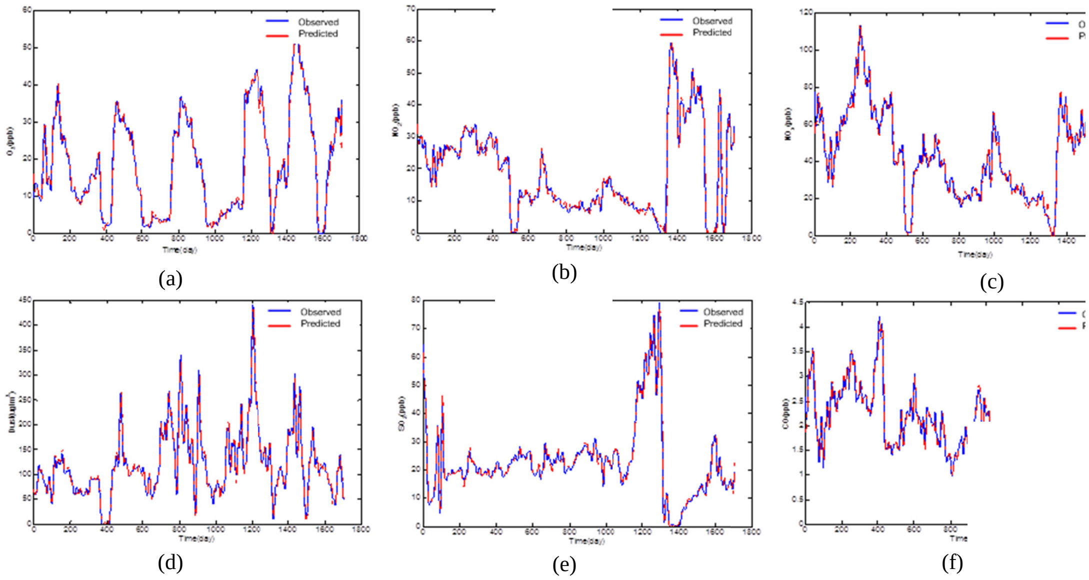

Fig. 4: ANN simulation results for (a) O_3, (b)NO_2, (c) NO_x, (d) Dust, (e) SO_2 and (f) CO, Kermanshah, Iran-2006-2011.

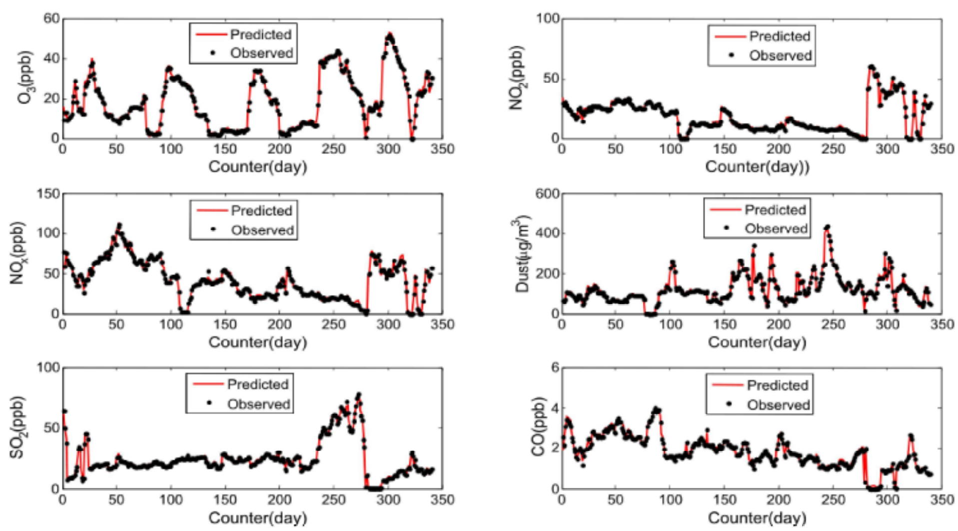

Fig. 5: Comparison between observed and ANN predicted data for test data set.

Fig. 5 illustrates a comparison for testing set between the experimental results and the ANN model prediction for the pollutants monitored. There is a high agreement between model prediction and the experimental data for the test data set, which were not used during model development.

In a research work carried out by Fernando and coworkers [5], they used ANN for air quality prediction. They found reasonable agreement between the calculated and observed values. Hooyberghs and coworkers [3] used neural network tool to forecast the daily average PM_{10} concentrations in Belgium. The most important input variable found was the boundary layer height. By extending the model with other input parameters they were able to increase the performance only slightly.

Wang and his coworkers [19] examined relationships between the formation and the movement of the dust storms in East Asia by numerical simulation and synoptic analysis of dust emission and transport. The simulated results are verified by observations and satellite images. It is found that the dust model has considerable skill in the prediction of Asian dust storms, but dust concentrations in regions of rainfall are generally overestimated as wet deposition was not considered in the model. An integrated dust storm modeling system was also developed by Sun and coworkers [20], for the prediction of dust storms. The system coupled a wind erosion scheme, a dust transportation model with a geographic information database. The system could be

Table 3: List of mean value of climate parameter and pollutant gases

Temperature							
Average	Maximum	Minimum	Pressure	Rain precipitation		Sunny Hours	
16.4	24.6	7.8	868.3	1		7.8	
Snowing days			Cloudiness Value			Relative Humidity %	
Snowing	Rainy	6.5	12.5	18.5	6.5	12.5	18.5
0	0	2	3	3	85	10	12
Wind (00-3:30)		Wind (03-6:30)		Wind (06-9:30)		Wind (09-12:30)	
Direction	Speed	Direction	Speed	Direction	Speed	Direction	Speed
Constant	0	Constant	0	Constant	0	SW	4
Wind(12-15:30)		Wind(15-18:30)		Wind(18-21:30)		Wind(21-00:30)	
Direction	Speed	Direction	Speed	Direction	Speed	Direction	Speed
W	4	W	4	W	4	Constant	0
O_3(ppb)	NO_2(ppb)	No_x(ppb)		Dust(µg/m^3)		SO_2(ppb)	CO (ppm)
18.6	18.8	41.2		121.4		22.8	1.8

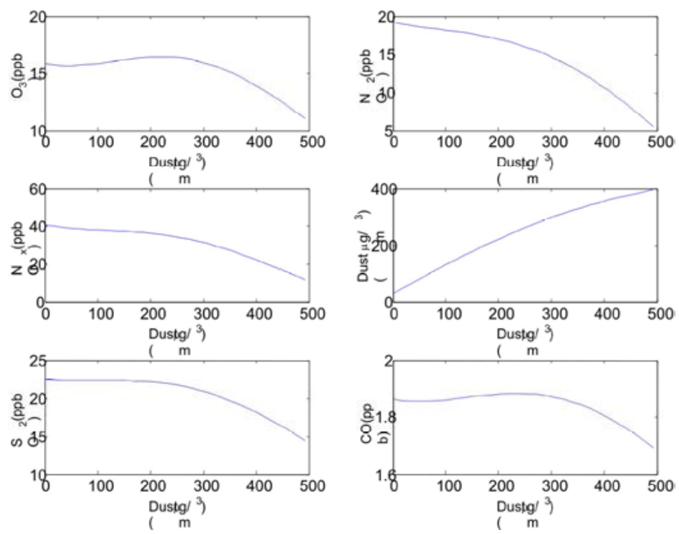

Fig. 6: Effects of increasing dust value on the gaseous pollutants at constant values of the other variables presented in Table 3.

used for the prediction of dust emission rate and dust concentration associated with individual dust storm events.

Interaction of Dust with the Gaseous Pollutants: In order to study dust interaction with the gaseous pollutants, all mean values of input data were evaluated. The values are listed in Table 3. In this table, metrological parameters includingtemperature, pressure, rain precipitation, sunny hours, snowing days, cloudiness value, relative humidity and direction and speed of wind during day and night (every 210 min) were selected to be studied. It must be noted that the pollutants data measured in three continuous days were also selected for the investigation.

The effect of increasing in dust on the pollutants measured is shown in Fig. 6. In this stage, the pollutantsvalues are the predicted values by ANN. Dust had a decreasing impact on the gaseous pollutants. As shown in the figure, increase in dust up to 400 µg/m^3, caused about 60 % decrease in the gaseous pollutants. It might be due to adsorption of the gaseous pollutants on the dust particles. This may be attributed to physical and chemical interaction of gases with functional groups of dust surface.Generally, The atmospheric chemical composition is affected by the interaction mechanisms among gases and particulate matter through a wide range of chemical reactions that can occur with the aid of particulate matter (e.g. particles act as reacting or absorbing surfaces) or be influenced by the presence of

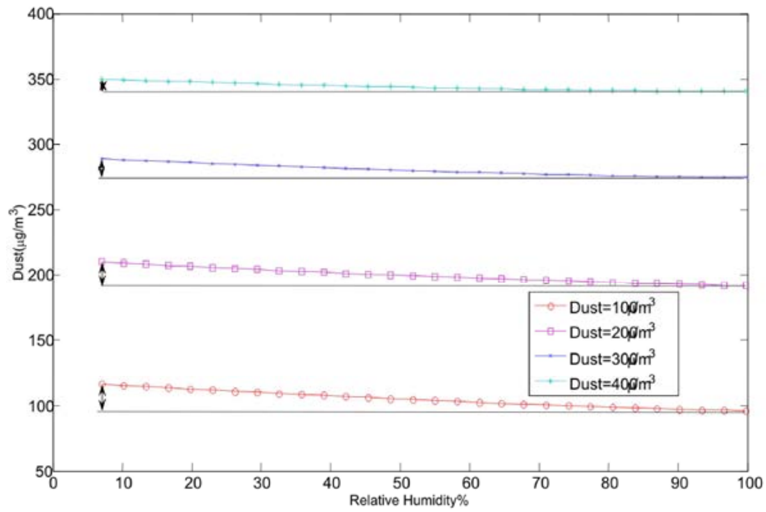

Fig. 7: Effects of relative humidity on dust at different initial values

particulate matter in the atmosphere (photochemical reactions). Physical and chemical processes are also bonded in an interactive way that often leads to the influence of the radiation budget, cloud physics and the warming or cooling of the lower atmospheric levels [18].

Another important parameter affecting the gaseous pollutants is relative humidity (RH) which has a controlling effect on reduction of dust pollution. In order to assess the effect of RH on dust levels, RH varied from 0 to 100 % at four different dust levels (100, 200, 300 and 400 µg/m^3). Fig. 7 represents the effect of RH on dust. The concentration of dust ispredicted by ANN. In this figure, this reduction is approaching to a constant value which means that relative humidity can only reduce a limited value of dust particles.Originally, humidity affect such that some dust particles coagulate and settle on the ground. As a result, it could be inferred that sensitivity of dust to relative humidity decreases with an increase in initial dust value.

Spellman [21] predicted surface ozone concentration using surface meteorological variable as predictors by a multi-layer perception neural network for five locations in the United Kingdom. He concluded that the relationship between weather and ozone is highly complex and non-linear in his studies.

CONCLUSION

Neural network model was useful and applicable for forecasting dust levels few days before dust storm occurrence as a reliable warning system for given sites. Selection of the variables by stepwise regression as the inputs of ANN model was a feasible methodology. The ANN model prediction showed a very good agreement with the actual data. The dust occurrence had a decreasing impact (up to 60 %) on the gaseous pollutants in the urban areas. Relative humidity (RH) and dust level also showed an interactive effect, a decrease in RH by increasing in dust and vice versa.

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