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Investigation the ability of artificial intelligent based predicting tool in modeling the effects of atmospheric parameters on air pollution

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ABSTRACT

Prediction of the amount of air pollution on the basis of atmospheric parameters is necessary. Complex relation between atmospheric parameters and the amount of air pollution has been evaluated. So, such a complex relation makes it difficult to simulate the amount of air pollution through mathematical models. Simulation of the amount of air pollution was carried out by Artificial Neural Networks (ANNs). The effects of atmospheric parameters (temperature, pressure, precipitation, and wind speed) as well as the day of week on the amount of air quality index (AQI) were simulated by ANN. Atmospheric parameters were generated using meteorological data collected during 90 days from 23th September to 21th December of 2014 in city Tehran. AQI was measured in terms of 4 types of air pollutants (carbon monoxide, sulfide dioxide, particulate pollutants, and nitrogen dioxide).

KEYWORDS

Air pollution;
AQI;
ANN;
Atmospheric parameters.

INTRODUCTION

Air pollution is one of the controversial issues that resulted from widespread industrial activities of human kind. Air pollution is resonated in cold days due to air inversion phenomenon and severely threats public health. Accordingly, prediction of the amount of air pollution on the basis of atmospheric parameters to face this dangerous phenomenon is necessary.

Arden Pop et al. reported the relation between air pollution and lung cancer as well as cardiopulmonary mortality[1]. In another study, Arden Pop et al. reported that increase in fine particulate air pollution resulted in increase of all-cause, cardiopulmonary, and lung cancer mortality. They also reported that the coarse particulate and total suspended pollutants have no effect on mortality[2].

The most important issue ahead is to find an accurate and reliable method to predict the amount of air pollution in a certain time duration and geographic region which is called city's territory.

As yet, several mathematical models were developed to simulate the amount and dispersion of air pollution. Karpinnen et al. developed a model to evaluate the traffic volume, emissions from fixed and mobile sources, and atmospheric dispersion. Dispersion model was developed based on a hybrid system of urban dispersion modeling and road network dispersion[3]. Frohn et al. developed a 3-D model based on numerical methods[4]. Bergin et al. used Monto-Carlo method to investigate the effects of uncertainty in air parcel trajectory path, emissions, rate constants etc. on the results of photochemical trajectory model[5]. There are some other models such as prognostic air pollution model[6] and Danish Eulerian hemispheric model[7].

Finding the non-linear relationships between input and output data of a phenomenon to develop a mathematical model is a challenging task and in some cases it is impossible due the complexity of the process. Complex relation between atmospheric parameters and the amount of air pollution has been evaluated. So, such a complex relation makes it difficult to simulate the amount of air pollution through mathematical models. However, methods based on artificial intelligent systems such as artificial neural networks (ANN), fuzzy inference system, and adaptive neuro-fuzzy inference system can be applied for modeling of these complex input-output relations.

ANNs store the obtained knowledge from analyzing the training dataset. As a result, it canmodel the complex input-output dependencies.

The aim of this study is to find a model to predict the amount of air pollution in different days. This study structured as follows. First, data gathering was represented. Further, ANN was introduced. Then the effects of atmospheric parameters (temperature, pressure, precipitation, wind speed) as well as the day of week on the amount of air quality index (AQI)were simulated by ANN.

METHODS AND MATERIALS

Data gathering

Atmospheric parameters were generated using Metheorological data collected during 90 days from 23th Septemberto 21th December of 2014 in city Tehran[8]. Estimates of amount of perticipation was determined according to the last 24 h percipation of each day.

The amount of pollution concentration was obtained from Tehran Air Pollution Control[9].

It is important to note that to predict the amount of air pollution in day n, the operative parameters of day n-1 were used.

The effect of traffic and the industrial activities on the amount of air pollution is important. So, one of the input parameter is the day of week.

AQI was measured in terms of4 types of air pollutants (carbon monoxide, sulfide dioxide, particulate pollutants, and nitrogen dioxide).

Artificial neural network (ANN)

A neural network is, by definition, a system consists of processing elements, called neurons, which are connected to a network by a set of assigned weights. Architecture, magnitude of the weights and the processing mode of operation are important parameters, which will construct a network. Neuron is a processing element that takes a number of inputs as well as their weights, sums them up, adds a bias and uses the results as an argument for a transfer function. A transfer function is assigned to each neuron that determines the value of the outputs. Several common types of transfer functions such as sigmoid, hyperbolic tangent and linear would be applied in different conditions. It is worthwhile noting that for the case of non-linear input-output relationships, the sigmoid function is widely used[10].

Back propagation neural network is a type of ANN that consists of input layer, output layer, and hidden layers. The input layer has four nodes, which corresponded to five input parameters.

Model validation

The accuracy of models was measured using correlation coefficient index (R^2) calculated as follow:

$$R^2 = 1 - \sum \frac{(y_{exp.} - y_{pred.})^2}{\Sigma (y_{exp.} - \bar{y})^2} \quad (1)$$

$$\bar{y} = \frac{\Sigma y_{exp.}}{N} \quad (2)$$

Where $y_{exp.}$ and $y_{pred.}$ are experimental and predicted values, respectively.

RESULTS AND DISCUSSION

The operating 90 days were divided into 3 sections: (I) 23th September to 22th October, (II) 23th

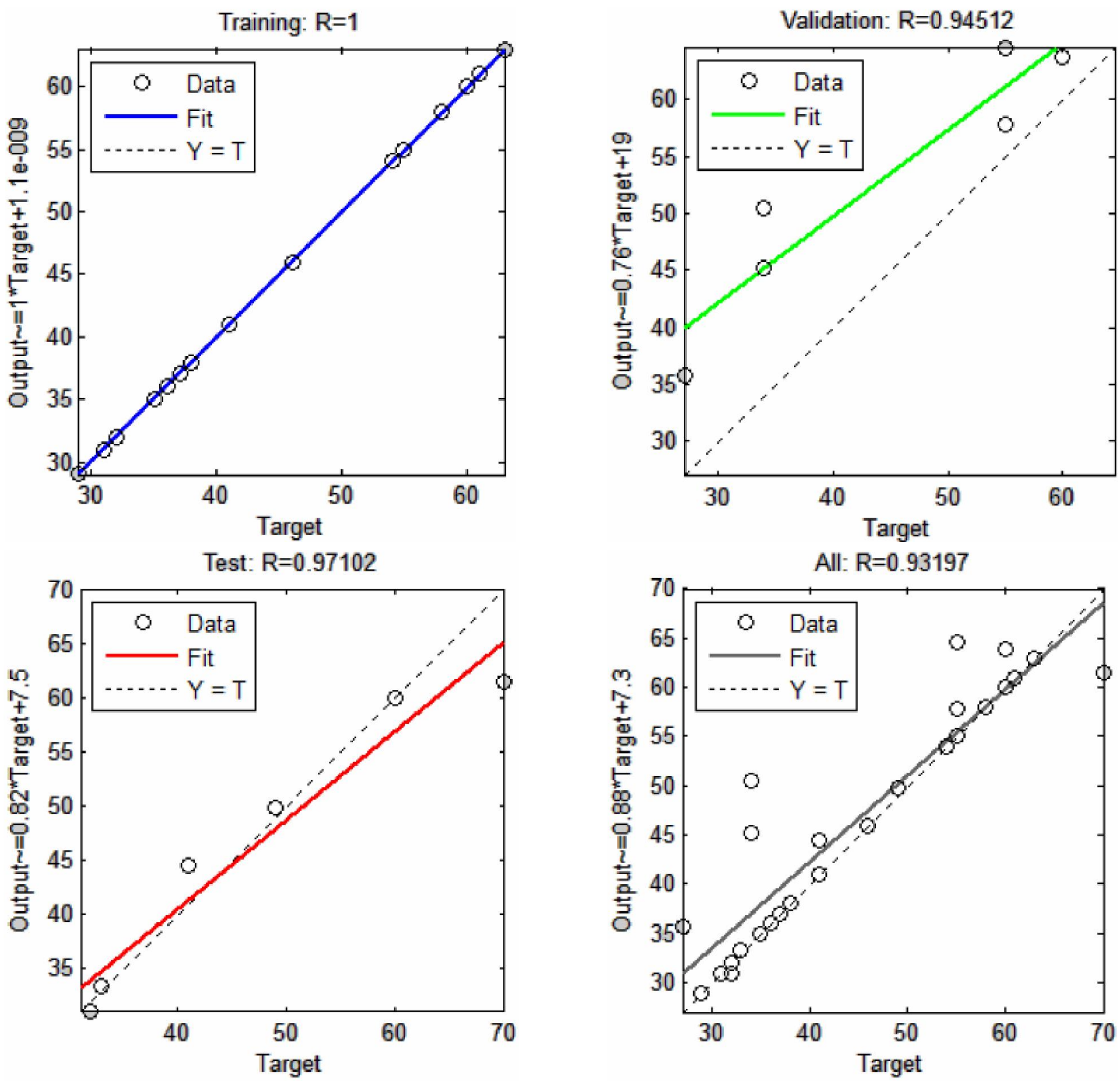

Figure 1 : Predicted data vs. experimental data from 23th september to 22th october

October to 21th November, and (III) 22th November to 21th December.

Carbon monoxide

To predict the AQI in term of concentration of CO from 23th September to 22th October a network with three hidden layers and 30-20-30 neurons in hidden layers was generated and trained. In Figure 1, the predicted data by the network vs. experimental data were plotted. The R^2-value of training, testing, validation, and total data have been shown.

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To predict the AQI in term of CO concentration from 23th October to 21th November, a network with 10-20-10 neurons in hidden layers was trained and tested. The R^2-value of training dataset was 1 which implies exact agreement between predicted and experimental data. The R^2-value of testing and validation dataset was 0.9845 and 0.8135, respectively. For data obtained from 22th November to 21th December, another network with three hidden layers and 10-20-10 neurons in hidden layers was selected and trained. The R^2-value for testing and validation data set was 0.9576 and 1, respectively. Accordingly, the optimum model was the network which was applied or prediction the CO concentration from

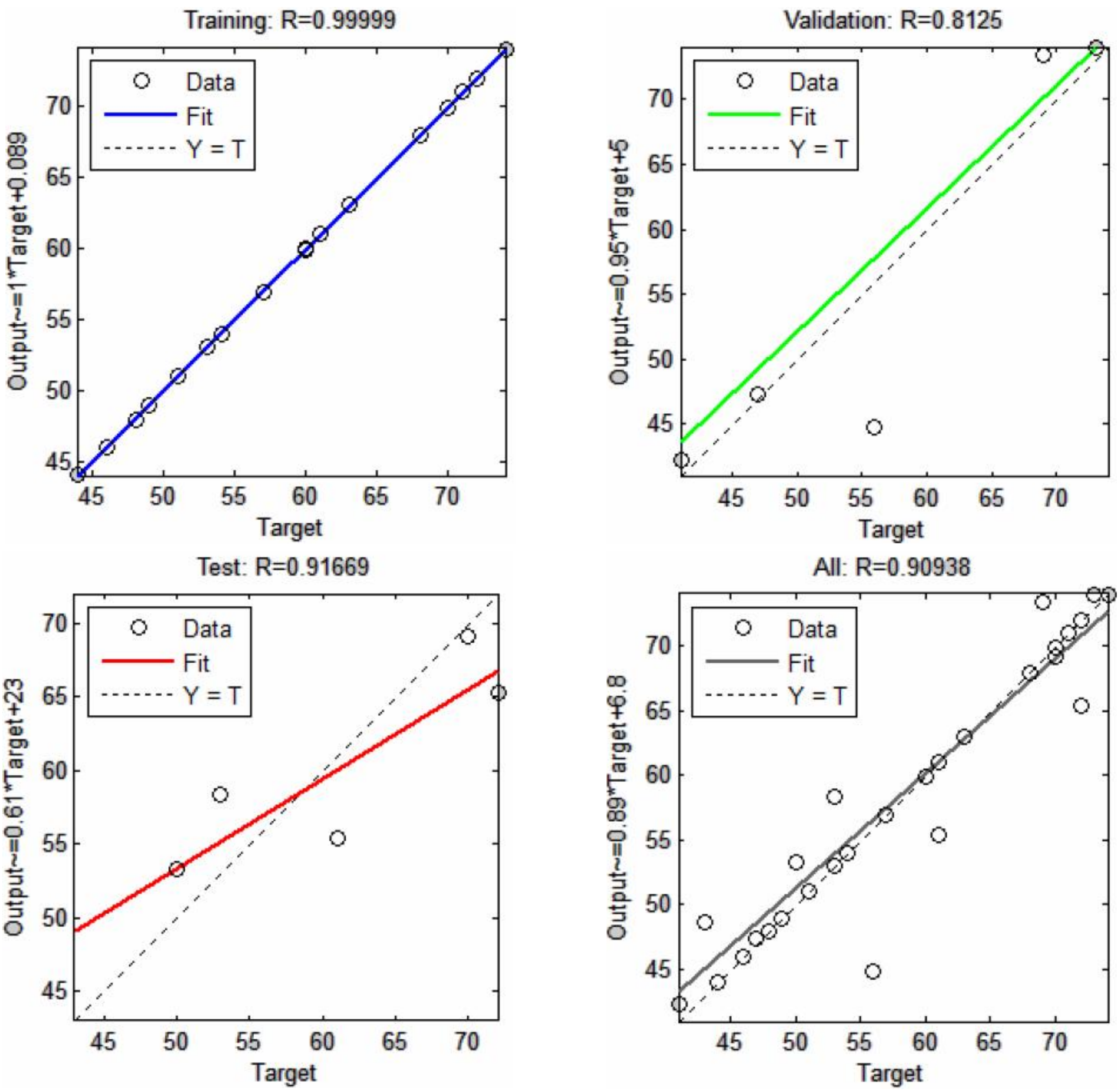

Figure 2 : Predicted data vs. experimentalAQI based on NO2 concentration from 23th September to 22th October

22th November to 21th December. According to the developed models, the minimum predicted AQI based CO concentration was 29.6 at October 19. Further, the maximum AQI based CO concentration was 63.6 at October 24.

Nitrogen dioxide

In Figure 2, the predicted AQI based on NO_2 concentration by the network vs. experimental data related to training, testing, validation, and total datasets from 23th September to 22th October 'were plotted. The ANN of this period of time for NO_2 concentration was a network with three hidden layers.

In Figure 3, the predicted AQI using the generated model was plotted in terms of the normalized participation and the speed of wind. As is shown, the relation between NO_2 concentration and operative parameters was very complicated and hard to simulate by mathematical models. The minimum value of AQI in this period of time was 46.7 which associate with wind speed of 0.45 and participation of 0.15. Similarly, the maximum value was 69.8 associate with wind speed of 0.95 and participation of 0.23 while the other operative parameters were ixed at their mean values.

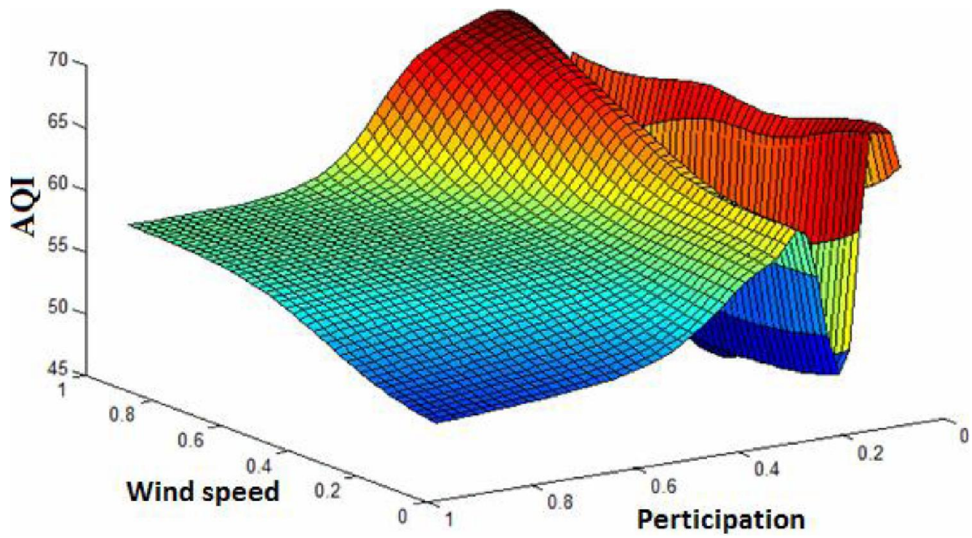

Figure 3: The predicted AQI based on NO2 concentartion in terms of wind speed and perticipation from 23th September to 22th October 2014

TABLE 1 : R^2-valuse of data predicted by the generated models for the NO_2 concentration

Period of time	R^2			
	Train	Test	Validation	Total
23th October-21th November	1.0000	0.8031	0.9514	0.9775
22th November-21th December	0.9999	0.9227	0.8371	0.9306

TABLE 2 : The performance of ANN in prediction the SO_2 concentration

Period of time	R^2			
	Train	Test	Validation	Total
23th September to 22th October	1.0000	0.9593	0.9641	0.9556
23th October-21th November	1.0000	0.8863	0.9267	0.9460
22th November-21th December	1.0000	0.9249	0.8556	0.9400

In Figure 4, the values of AQI based NO_2 concentration that were predicted by a network with 30-20-30 neurons in hidden layers were plotted against the experimental values within22 November to 21 December. In TABLE 1, the R^2-values related to the models of two periods of times have been shown.

Sulfur dioxide

For prediction the values of AQI based on SO_2 concentration, three networks with 30-20-30 neurons in hidden layers were generated. In TABLE 2, the R^2-values related to the models of three periods of times have been shown.

In Figure 5, the values of AQIthat were predicted by the trained model have been plotted in terms of the normalized pressure and the speed of wind within 23th October to 21th November 2014. The precipitation and temperature were fixed at their mean values.

Particulate pollutants

Similar to the other air pollutants, the AQI values in term of particulate pollutants were simulated by the artificial network within three time periods.

In these three periods of time, the network generated and trained for 23th October to 21th November with 30-20-30 neurons in hidden layers predicted the AQI value with higher preciseness compared to the other two time periods. The R^2-value for test and validation was 0.996 and 0.967, respectively.

In Figure 6 the predicted values of AQI were plotted against the operative parameters within 22 November to 21 December. It is found out that there are non-linear relation between AQI and atmospheric parameters.

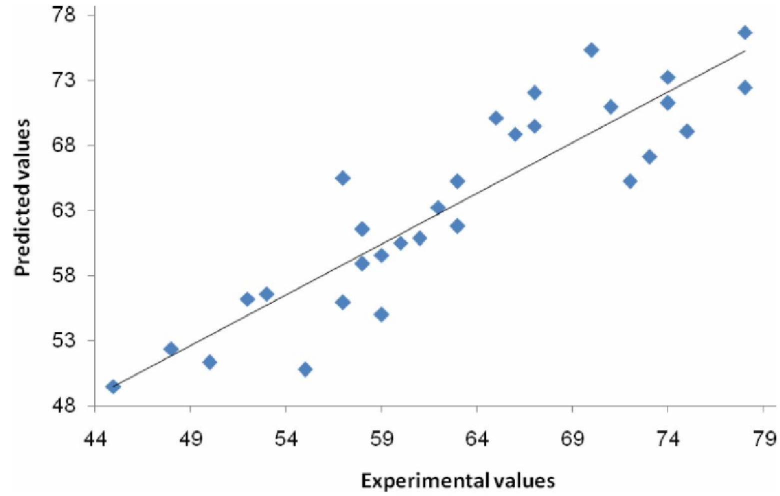

Figure 4 : The predicted vs. experimental values within 22 November to 21 December

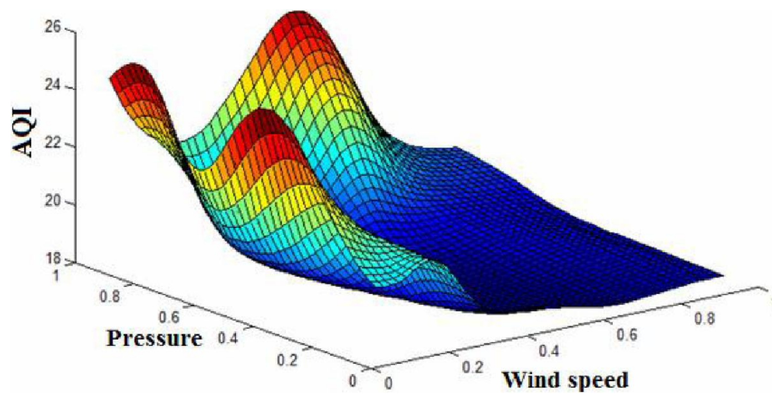

Figure 5 : The predicted AQI based on SO2 concentartion in terms of wind speed and pressure from 23th October to 21th Nonember 2014

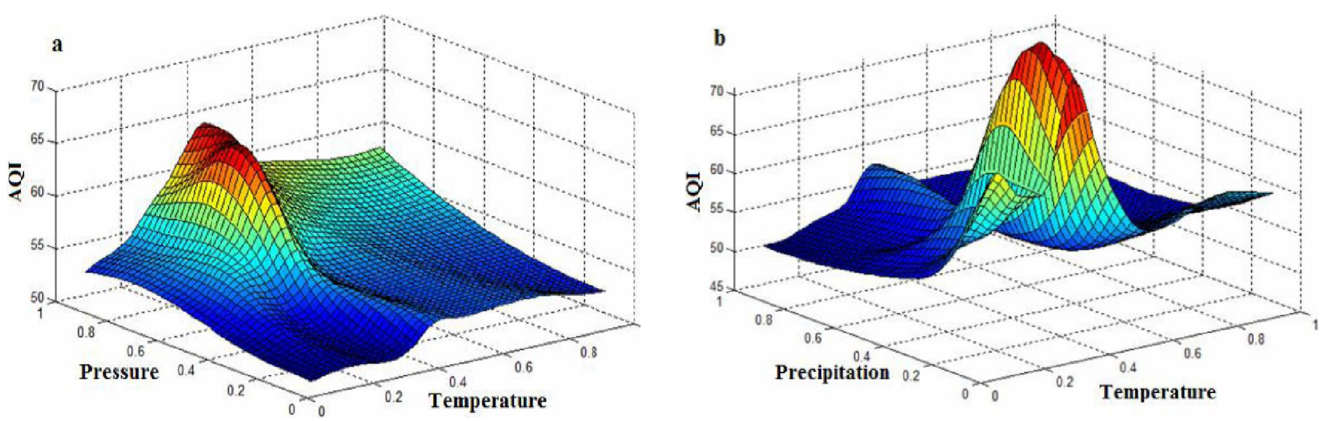

Figure 6 : The predicted AQI vs. atmospheric parameters: (a) pressure-temperature and (b) precipitation-temperature from 22 November to 21 December 2014

CONCLUSIONS

The operating 90 days were divided into 3 sections. The amount of air quality index (AQI) in terms of nitrogen dioxide, sulfur dioxide, carbon monoxide, and particulate pollutants were simulated using by artificial neural network (ANN) with three hidden layers and different neurons in each hidden layer. Several neural networks were defined and trained for prediction the values of AQI. The trained networks have high ability in prediction of the amount of air pollution. So, it is proved that ANN would generate a robust model for prediction and control air pollution in big cities in terms of atmospheric parameters and the day of work.

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Nomenclature

ANN	Artificial neural network
N	Number of data
R^2	Correlation coefficient index
$y_{exp.}$	Experimental values
y_{pred}	Predicted values

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