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Sulfur dioxide AQI modeling by artificial neural network in Tehran between 2007 and 2013

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Abstract

Background: Air pollution and concerns about health impacts have been raised in metropolitan cities like Tehran. Trend and prediction of air pollutants can show the effectiveness of strategies for the management and control of air pollution. Artificial neural network (ANN) technique is widely used as a reliable method for modeling of air pollutants in urban areas. Therefore, the aim of current study was to evaluate the trend of sulfur dioxide (SO_2) air quality index (AQI) in Tehran using ANN.

Methods: The dataset of SO_2 concentration and AQI in Tehran between 2007 and 2013 for 2550 days were obtained from air quality monitoring fix stations belonging to the Department of Environment (DOE). These data were used as input for the ANN and nonlinear autoregressive (NAR) model using Matlab (R2014a) software.

Results: Daily and annual mean concentration of SO_2 except 2008 (0.037 ppm) was less than the EPA standard (0.14 and 0.03 ppm, respectively). Trend of SO_2 AQI showed the variation of SO_2 during different days, but the study declined overtime and the predicted trend is higher than the actual trend.

Conclusion: The trend of SO_2 AQI in this study, despite daily fluctuations in ambient air of Tehran over the period of the study have decreased and the difference between the predicted and actual trends can be related to various factors, such as change in management and control of SO_2 emissions strategy and lack of effective parameters in SO_2 emissions in predicting model.

Keywords: Sulfur dioxide, Neural networks, Air quality index, Tehran.

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Introduction

Air pollution is a serious challenge for human health and annually millions of tons toxic pollutants due to human activities are released into the atmosphere (1). Therefore, many of the metropolitan cities of the world are exposed with the challenge of air pollution that causes citizens exposure to air pollution and has created health problems. With increase in population growth and industries, the possibility of air pollution gradually increased, such that the most likely outcome is threat of human health and environmental damage (2). Tehran is one of the most polluted metropolitan cities of the world. Much of this pollution in other countries is due to over population, the use of fossil fuels, heavy traffic, a lot of old vehicles, poor development of industry and other pollution related to the geographical location of Tehran to the southern slopes of the Alborz mountains and surrounded by mountains at the north and east. In addition, the impact of climate conditions, such as calm winds and stable weather and lack of rainfall are highly effective in Tehran, thus intensifying air pollution (3). Several pollutants are involved in creating and intensifying air pollution; sulfur dioxide (SO_2) is one of the most important air pollutants and one of the criteria of pollutants of air quality index (AQI). Large amounts of SO_2 are emitted from diesel vehicles (all commercial vehicles and buses), especially in congested downtown areas (4,5). Generally, SO_2 emissions in a region is related to various factors, such as economic growth, pollution control laws, fossil fuel consumption and etc (6). The importance of SO_2 is found in the wide range of consequences of air pollution and climate changes. Generally, three major environmental consequences of SO_2 pollution will be considered: photochemical smog, acid rain, and global climate change (7). Results of a study in China showed that SO_2 emissions have increased to 53% in the period between 2000 and 2006, which is approximately 3.7% annual increase (4). In Klang Valley of Malaysia, the trend of SO_2 concentration showed significant increase in high traffic stations (8). The trend of SO_2 in seven major cities of Korea between 1989 and 2010 showed that much higher concentrations of SO_2 occurred in winter (9). Considering the importance of air pollution, the use of preventive strategies and predicting is very important. Air pollution predicting can be used through models and available tools. Nowadays, modeling tools are widely used in many scientific fields, especially in environmental sciences, such as air pollution (10). Artificial neural networks (ANN) developed in recent years, have been used to model pollutant concentrations with promising results (11-13). This is regarded as an intelligent, cost-effective approach and has received much attention in environmental engineering. ANN is an information processing paradigm that is inspired by the biological nervous systems, such as the brain processing formation. It is composed of a large number of highly inter connected processing elements (neurons) working in unison to solve specific problems. The goal of this network is to create a model that can correctly map the input to the output using historical data, so that the model can then be used to produce the output when the desired output is unknown. An ANN has a parallel distributed structure and consists of a set of processing elements called neurons. The ANN structure consists of input layer which receives data, output layer to send computed information and one or several hidden layers lying the input and output layers. According to the architecture, all or a part of the neurons in a layer are connected with all or a part of the neurons of the previous and next layer. The number of hidden layers and neurons of each layer depends on the specific model, convergence speed generalization capability, physical process, and the training data that the network will simulate (14). Concentration variation in predicting air pollutants using neural network was used in the early 1990s and for the first time by Boznar et al who used it to predict the concentration of SO_2 in industrial areas of Slovenia (11). The ability and power of neural networks to learn the complexity of communications of air pollution systems, has led to the use of neural network model to examine environmental issues increase. Sahin et al (15) carried out a study using neural networks and nonlinear regression model for the concentration of SO_2 in Istanbul. The results of this study showed that neural network was better than nonlinear regression. Mok and Tam used ANN to predict the daily SO_2 concentration. The promising results showed that ANN could be used to develop efficient air-quality analysis and prediction models in the future (16). An autoregressive moving average model (ARMA) and time series forecasting of SO_2 in Tehran were used for the period of 2000 to 2005. The results proved that ARMA model can provide reliable, satisfactory predictions for time series and SO_2 emission was significantly high for stationary sources as compared to other pollutants (17).

Trend of air pollutant can show that strategy of air pollutant emission control has been useful or not. Considering the above and the proper performance of the neural network, the aim of this study was to investigate SO_2 AQI trend between 2007 and 2013 and forecasting model in Tehran using neural network.

Methods

Study area

The present study was carried out in Tehran. Tehran is located at the foot of the Alborz mountains, south of the Caspian Sea and is the largest urban area of Iran that has the highest population (8 700 000 in 2011). The city is also ranked as one of the largest cities in Western Asia and 19th in the whole world. As in other large cities, Tehran is faced with serious air quality problems. In general, 20% of the total energy of the country is consumed in Tehran. Compounding Tehran's air pollution problem is its geographical location. With the location of 35° 41' N - 51° 25' E and altitude of 1000 to 1800 m above mean sea level, Tehran is located in valleys and is surrounded on the north, northwest, east and southeast by high to medium high (3800 to 1000 m) mountain ranges (18).

SO_2 data

The daily SO_2 AQI and concentration between 2007 and 2013 were obtained from 16 air quality monitoring stations that belonged to the Department of Environment (DOE). In monitoring stations of the DOE, UV fluorescence analyzers (model AF22M of Environment SA, France) were used to measure SO_2. Complete datasets would have contained 2550 days measured values.

Methodology for ANN implementation

The nonlinear autoregressive (NAR) neural network through Matlab software (R2014a) was used for the SO_2 trend and forecasting. As previously mentioned, the implementation of ANN consists of several phases. Our conducted procedure is described as follows:

Data normalizing

For data normalizing, data convolution with Gaussian function was used to move a window while maintaining the nature of the data, and largely eliminates unwanted noise in the data. Averaging window techniques was used and 31 windows were chosen for noise removal.

Network structure

Considering the existing number of hidden layers and number of neurons in each layer, the number of choices available for network design increase, therefore the design and testing of all cases is actually not feasible. Cybenco proved that a hidden layer if having sufficient number of neurons could provide all the certain conditions (19). Depending on the appropriate inputs, the use of simpler structure is more favorable and network with one or two hidden layers can actually be able to solve a variety of issues. However, a program of data processing with the aim of finding the best neural network architecture by trial and error according to the number of layers was designed with the number of architectures (20,21). Therefore, the network consists of two hidden layers obtained with 50 neurons in the first hidden layer and 50 neurons in the second hidden layer and Bayesian regularization algorithm is used as shown in Figure 1.

Transfer functions

Tansig transfer functions were used each time separately to obtain the best combination of transfer and linear function for realizing a good approximation of every type of functions.

Training/Test set

The maximum number of training generations of 500 was considered when there was no significant change after the fifth generation of network training. During training of network, 70% of data was considered as the training and 30% as the test.

The error diagram and validation for different repeats to simulate SO_2 based on mean-square error is as shown in Figure 2. It is clear that the selected network has very high accuracy. Figure 3 shows the correlation between actual output and estimated output through network and R = 0.999 represents high correlation between actual data and estimated data.

The results for network training are as shown in Figure 4. Test data (green) completely overlap the actual data (blue) and the used model shows that error (orange) is also very low. Therefore, the results show a high power of network to predict the time series trend of SO_2.

Data input

For simulation and forecasting of SO_2 AQI, 810 days were used as input data and the next 90 days was predicted.

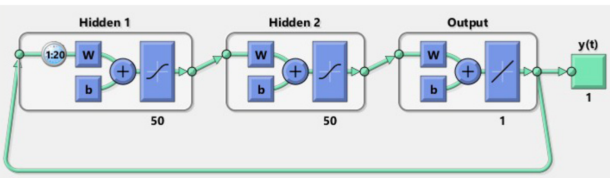

Figure 1. Artificial neural network.

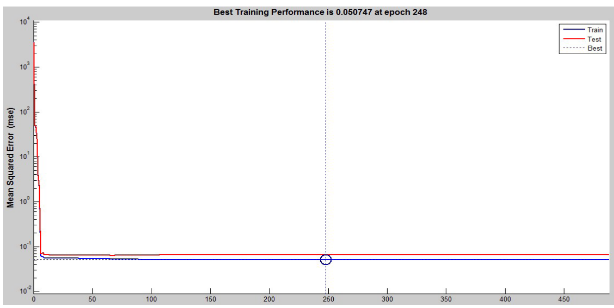

Figure 2. The training error rate and validation for SO_2 simulation based on mean-square error.

Results

So_2 pollution data

The seasonal and annual mean concentration (standard deviation) of SO_2 in Tehran is shown in Table 1. The lowest annual mean concentration of SO_2 was 0.018 ppm in 2013 and maximum was 0.037 ppm in 2008. Winter of 2007 had the highest mean concentration of SO_2 (0.049 ppm) among the seasons.

Trend of SO_2 AQI

AQI trend of SO_2 in Tehran for the period of 7 years (2007 to 2013) is as shown in Figure 5. Trend of SO_2 in several days did not have a constant pattern over the time that has been studied, especially between 2007 and 2010 (1400 days), there were a lot of fluctuations, but in the last three years (2010 to 2013), trend and fluctuations regularly declined.

For forecasting of SO_2 AQI, 810 days were used as input data and the result of 90 days forecasting is as shown in Figure 6. It can be observed that the predicted trend is

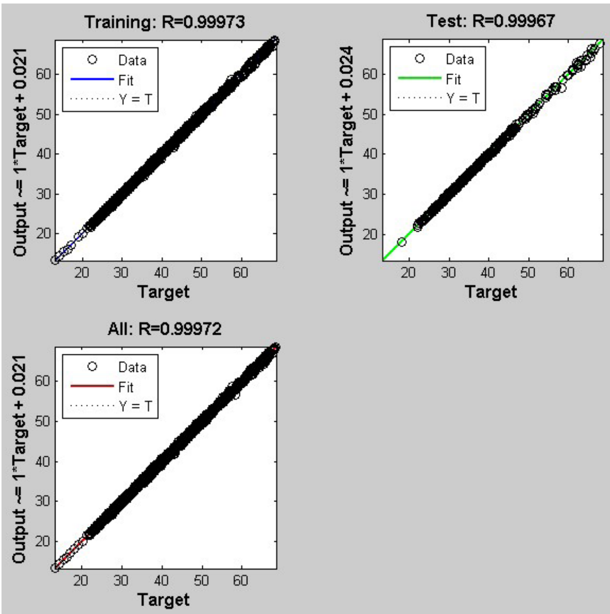

Figure 3. Correlation between actual output and estimated output by network.

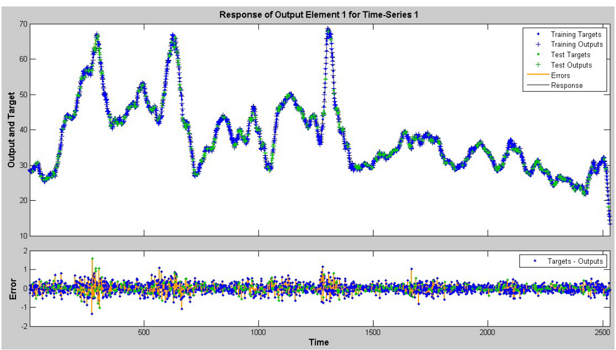

Figure 4. Comparison simulation of trend with actual trend of sulfur dioxide AQI in Tehran.

Table 1. Seasonal and annual mean concentration of SO_2 (unit: ppm ± SD)

Year	Season				Annual
	Spring	Summer	Autumn	Winter	
2007	0.019± 0.003	0.022± 0.006	0.034± 0.006	0.049± 0.009	0.033± 0.02
2008	0.029± 0.003	0.033± 0.004	0.033± 0.009	0.034± 0.01	0.037± 0.01
2009	0.021± 0.003	0.028± 0.003	0.027± 0.005	0.029± 0.003	0.025± 0.005
2010	0.033± 0.004	0.030± 0.003	0.035± 0.012	0.023± 0.006	0.033± 0.018
2011	0.021± 0.002	0.023± 0.002	0.026± 0.004	0.025± 0.004	0.024± 0.004
2012	0.020± 0.002	0.023± 0.003	0.021± 0.003	0.023± 0.004	0.022± 0.003
2013	0.020± 0.002	0.018± 0.002	0.016± 0.003	0.020± 0.004	0.018± 0.003

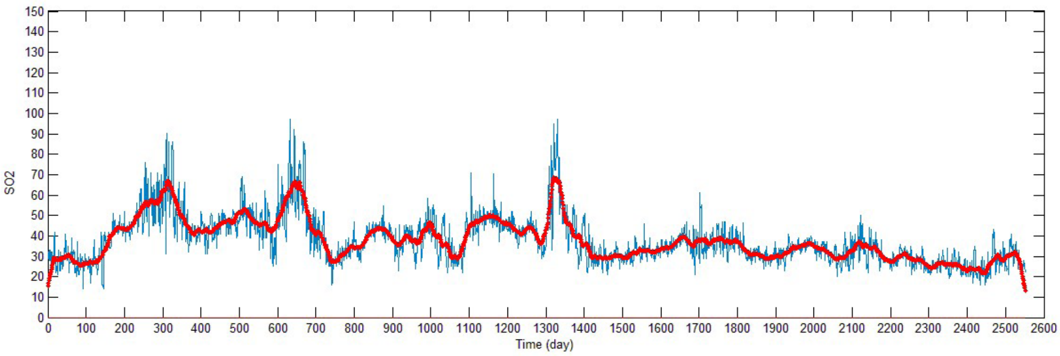

Figure 5. Trend of SO_2 AQI between 2007 and 2013 in Tehran.

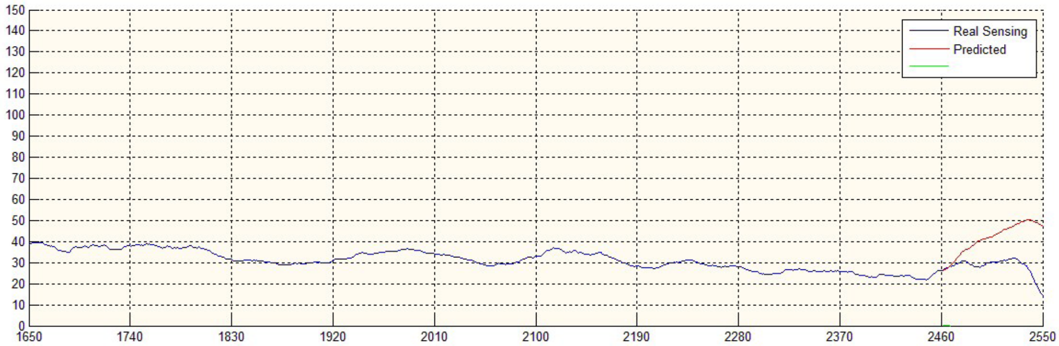

Figure 6. Forecasting of sulfur dioxide AQI trend using neural network.

higher than the actual trend and the predicted trend shows that SO_2 in air of Tehran can be increased in the future.

Discussion

Distributions of daily and annual mean concentrations for SO_2 for the period of 2007 to 2013 show that almost the annual average concentrations of SO_2 in ambient air of Tehran except 2008 were less than the standard (ppm 0.03). Also, in all the days studied, the concentration of SO_2 was not higher than the 24-hour standard (ppm 0.14). SO_2 emissions in a region is related to various factors and can vary in different situation and unlike this study, SO_2 emission between 2000 and 2005 in Tehran was considerably high for stationary sources as compared to other pollutants (17). The seasonal variation of SO_2 concentration was found from the daily means and presented in Table 1. The differences between the various seasons can be observed. The winter of 2007 had the highest SO_2 mean concentration (0.049 ± 0.009 ppm) among the other seasons. The high SO_2 emission is due to anthropogenic activities, such as domestic heating and industry and high concentration in winter could be the result of inversion.

There are several estimating and forecasting techniques. ANN was chosen for finding trend and forecasting of SO_2 in Tehran. Trend of SO_2 AQI over a period of 7 years is as shown in Figure 5 and can be observed despite daily fluctuations in the ambient air of Tehran, over the years studied, especially after 1700 days trend of SO_2 has decreased. Asrari et al (22) between 1995 and 2002 studied SO_2 trend in Tehran; this study showed high fluctuations and in most days they were much higher than the standard. This could depend on many factors, such as fluctuations in economic growth, better control of SO_2 sources, such as power plants near the city or refining diesel fuel quality and good management strategy in emissions control. The same study between 2005 and 2012 in relation with trend of SO_2 in Yangtze of China had been conducted and results showed a significant decline in SO_2 trend, especially after 2008 due to effectiveness of control and reduction of SO_2 emissions occurred at this area (23).

Predicted trend of SO_2 AQI using NAR model is as shown in Figure 6. It can be observed that predicted 90 days trend is higher than the actual trend. Therefore, we cannot predict the future trend of SO_2 in Tehran by this method. It could be the result of changes in management strategy in emission control or lack of effective parameters in SO_2 emissions in predicting model.

Conclusion

In this study, all the peaks of AQI were less than 100 showing good and moderate category. Trend of SO_2 AQI over the years studied in the ambient air of Tehran, has decreased. Difference between actual trend of SO_2 and predicted trend shows that the actual trend is well and unlike the predicted trend which declined and this can be related to various factors, such as good management and control of SO_2 emissions in Tehran.

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Ethical issues

Ethical issues (including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

Competing interests

The authors have declared that no competing interests exist.

Authors' contributions

All authors contributed equally, and all authors participated in the data acquisition, analysis, and interpretation. All authors critically reviewed, refined, and approved the manuscript.

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