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Prediction of the Air Quality by Artificial Neural Network Using Instability Indices in the City of Tehran-Iran

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ABSTRACT: Today, air pollution is a serious environmental problem becoming a global concern for human beings Air quality is influenced by emissions, meteorological parameters, and topography. The effect of these parameters can be predicted using statistical methods. In the current study, the data in the period of March 2012 to October 2013 are used. These data have been gathered from the stations of the Department of Environment and Air Quality Control Organization (Azadi and Sharif stations) in Tehran city. The main purpose was to predict the air quality of the next day and emissions of carbon monoxide and suspended particles under the influence of instability indices and meteorological parameters using the Artificial Neural Network. Results of the modeling process showed that the concentration of pollutants is strongly influenced by meteorological parameters. Also, prediction of the PM_{10} concentration of the next day using meteorological parameters (RMSE=29.03, R=0.76), instability indices and meteorological parameters (RMSE=28.13, R=0.76) were better than those obtained for AQI predicted by meteorological parameters (RMSE=20.81, R=0.50) and instability indices and meteorological parameters (RMSE=19.23, R=0.47). In general, the predicted values of PM_{10} and CO were better compared to AQI. It can be concluded that an artificial neural network couldn't load the model properly for AQI compared to PM_{10}.

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1- Introduction

Nowadays, air pollution is a serious environmental problem and global concern of human beings. It is one of the most important factors having an important impact on the quality of the environment and human life. Several studies indicated the relationship between air pollution and acute and chronic respiratory disorders as well as premature mortality [1]. The major emission sources of urban air pollution are road transport and increasing consumption of fossil fuels by domestic, commercial, and industrial sectors. In recent decades, excessive increase in the population, a great increase in the number of transportation vehicles, and also industrial rapid growth have made Tehran city facing various environmental issues, especially air pollution [2].

Prediction of air quality is one of the most required tasks for air quality management organizations in megacities such as Tehran. The predicting models are the best tools for air quality plans such as modeling, analyses of the measurement data, controlling criteria and forecasting, accidental release of pollutant, land-use planning, traffic planning, and planning for measurement programs. Some of the statistical models applicable for air quality prediction are ARIMA (Auto-Regression Integrated Moving Average), ANN (Artificial Neural Network), CMAQ (Community Multi-Scale Air Quality), Weather Research, and Forecasting Model with chemistry (WRF-Chem), Fuzzy Inference System, grey model, and hybrid methods. Among these models, ANN has some capabilities such as nonlinear mapping, robustness, and self-adaption, which make it suitable for forecasting purposes [3]. Artificial neural network (ANN) is inspired by the biological neural network. In the body of ANN, there are (a) an input layer, (b) many hidden layers, and finally (c) an output layer. The input layer receives the information of the output layer. At a simple glance at the model, a nerve should act as synapses. The inputs are multiplied by their weights to determine the signal strength and finally, a mathematical operator decides whether a neuron is activated or not; if yes the output is determined. Weights can be positive or negative and functions used for threshold level can be arctangent, arcsines, or a sigmoid function. There are many kinds of networks such as back-propagation (BP) neural networks, Kohonen self-organizing networks, Hopfield networks, radial basis function (RBF) networks, and multilayer perceptron (MLP). The application of ANN in forecasting air pollutants has been common since the early 1990s. For the first time, researchers in Slovenia [4] used this model for predicting the concentration of sulfur dioxide in polluted industrial areas. ANN has been applied to predict a wide range of pollutants concentrations and air quality at diverse time scales with very reasonable results. Comparing to other traditional statistical

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methods (regression and auto-regressive models), Artificial Neural Network (AAN) has better performance and abilities. Usually, the concentration of pollutants and ground level of meteorological data sets are used to develop prediction models by AAN. In fact, atmospheric instability is a very important factor to determine ventilation rate in an urban air shed [5]. The most important factor in the determination of accumulation and distribution of pollutants in the atmosphere is the determination of the frequent times that instability occurs in the atmosphere. Radio sound data can be helpful to predict the frequency of instability occurring in the atmosphere. From these data, specific indices are calculated showing the amount of convection and movement of air masses. In fact, instability condition is determined using a thermodynamic diagram known as skew-t. Generally, assessment of skew-t graph and data analysis can conclude items such as occurrence times of stability and instability in the atmosphere, patterns of meteorological elements on different atmosphere layers, determining some phenomena such as storms and hurricanes, and providing information for synoptic stations [6]. In general, it is possible to develop a better air quality prediction model using instability indices as input data for a specific model. These data present the vertical properties of the atmosphere. The objective of this study was to investigate the possibility of predicting Tehran's air quality and the PM_{10} and CO concentrations using a multi-layer perceptron neural network by recorded data of Iran's meteorological organization and Tehran air quality control organization between 2012 and 2013. In this study, for the first time, in addition to usual parameters (meteorological parameters), instability indices (atmospheric vertical profile data) are also used as the input of the network models which can be considered as an innovation of this work. Furthermore, the monthly and seasonal variations in the concentration of CO, $PM_{10,}$ and AQI were investigated.

2- Materials and methods

2.1. The study area

Tehran, with a population of more than 8.5 million, has been known as one of the most polluted cities in the world. It is located at a latitude of 35°41' North and 51° 25' East with an average altitude of 1139 meters above sea level with a semi-arid climate regime. As Fig.1 shows, based on municipal divisions, this city has 22 regions. Several factors such as geographical and meteorological, inversion in the cold season and vehicle traffics factors are affecting the air quality and air pollution of Tehran. According to Tehran's air quality control reports, the number of unhealthy days (>101) in 2012 was 61 days and 34 days until March 2013.

2.2. Data categorization and statistical

Selecting the input variables is a key factor for ANN-MLP as a predicting model. Irrelevant or noisy variables may have negative effects on network education trends, leading to uncertainty and complexity of the model leading to weak generalization ability. In the present study, the selection trend of independent input variables and indices factors affecting the estimation process of air quality prediction has been summarized in table 1. These data have been collected from 2012 to 2013. The instability indices including lifting condensation level (LCL), Showalter index (SI), and total index (TTI) were used as input data for predicting models. LCL is the elevation that if surface air arises spontaneously or by any force to reach to dew point and consequently be saturated. LCL is calculated by the method presented by Mark and Lawrence [7]. SHOW has been proposed by Showalter [8] as Eq. (1).

$$SI = T_{E\,500} - T_{P\,500} \tag{1}$$

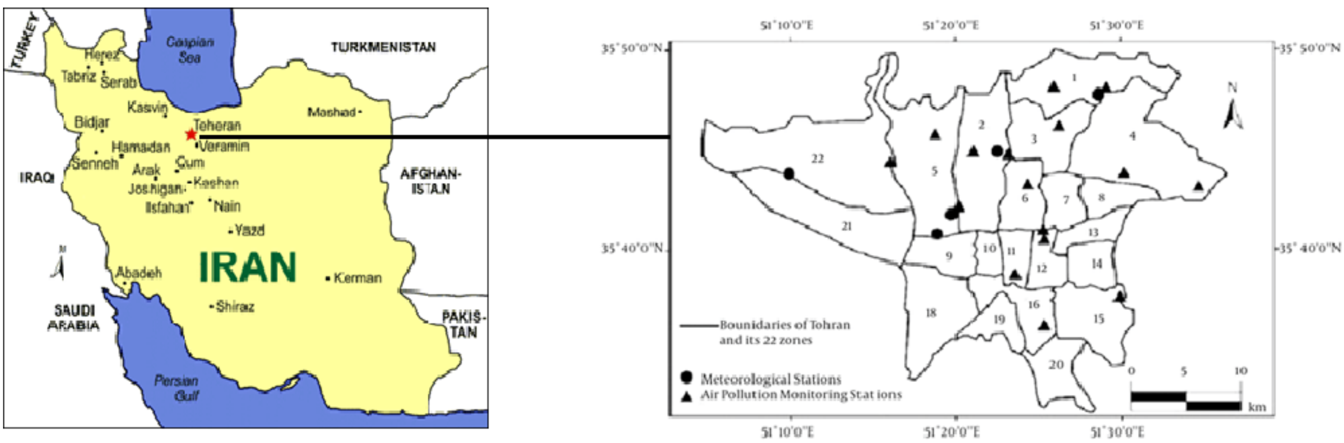


Fig. 1. The study area and meteorological stations.

Table 1. Description of variable input parameters and indices.

Main variables	Detailed variables
meteorological parameters	Wind speed (WS): meters per second (m/s) Wind direction (WD), degrees from true North Temperature (T), dry bulb temperature, °C Relative humidity (RH), (%)
Pollutant concentration	PM_{10} (particulate matter) CO (carbon monoxide)
Instability index	LCL (lifted condensation level) SI (Showalter Index) TT (Total Total index)

SI is Showalter index (°C), T_{E500} is the ambient temperature at 500 hpa (°C), T_{P500} is the parcel air temperature at 500 hpa (°C), provided that the parcel raised from an 850 hpa level. In general, values 0 to -3 of this index indicate low instability, and -4 to -7 values indicate high instability; values greater than -8 lead to extreme instability, and consequently air parcels will arise more and more. TT is an index that assesses the strength of the storm. This index is obtained from Eq. (2).

$$TT = \left(T_{850} - T_{500}\right) + \left(T_{d\,850} - T_{500}\right) \tag{2}$$

Where T and T_d are temperature and temperature of dew point, respectively at a certain level.

2.3. Artificial Neural Network (ANN)

Perceptron neural network is used for linear functions, but when it is comprised of a hidden layer, which is called multilayer perceptron (MLP), it can also be used for nonlinear functions and is mostly used to predict air quality. In this study, the trained network was MLP with an input layer, three hidden layers with 10 neurons, and an output layer for the prediction of PM_{10}, CO, and AQI values. This means that the output of each layer acts as input of the next layer. The real network response is determined by the output of the second layer. The neurons of the upper-layer are linked with neurons of the lower layers. The role of each neuron is determining the weights that are given to inputs of the network (*Net*) can be defined as Eq. (3).

$$Net = \sum\left(W_i X_I\right) \tag{3}$$

Where X_I is the input and W_i is the given weights. Then, this complex is passed through a function that is called 'the transfer function' which can be linear or nonlinear. The transfer function can be a sigmoid or tangent sigmoid function. In the present study, a sigmoid function is considered as a transfer function as bellow [9].

$$F\left(Net\right) = \frac{1}{1+e^{-NET}} \tag{4}$$

All the valid data set was containing 500 samples, which was divided into three sub-categories: 350 samples (70% of all samples) applied as a training set, 75 samples (15% of samples) considered as the validation set, and finally, the testing set was containing 75 samples (15% of all samples). As a known trend, training data set was used for the self-learning process of the model. The validation data set was applied for measuring the extending of the network. Finally, the test set was used for the assessment of the network performance after learning trend [10]. To avoid extreme shrinking of weights of the artificial neural network due to reaching an optimal training process, the data has been normalized in the range of 0 and 1 before being entered into the network, using Eq. (5).

$$Xnor = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

Where x is the original data, x_{min} and x_{max} are the rates of maximum and minimum of the original data. In this study, Levenberg Marquardt Algorithm (LMA) has been used for the training and learning process. LMA has been selected because of its faster convergence in the training process of medium-sized networks [11]. LMA has expressed as the Eq. (6):

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \tag{6}$$

where J is the Jacobian matrix deriving of error for each weight, μ is a number, e is vector error and I is the recognizing matrix. Parameter μ determines the weight of gradient descent [11]. To have proper ANN performance, statistics of root mean square error (RMSE) (Eq. (7)) and correlation coefficient (R) was used (Eq. (8)). RMSE ranged between

0 and 1; a closer value to zero shows high accuracy in the estimation of the concentration of pollutants and AQI. When the obtained R^2 gets closer to 1, the model has more accuracy in estimating the concentration of the pollutants and AQI.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - p_i\right)^2} \tag{7}$$

$$R^2 = \frac{\Sigma\left(P_i - \bar{P}\right)\left(O_i - \bar{O}\right)}{\left(\Sigma\left(\left(O_i - \bar{O}^2\right)\right)^{0.5}\left(\sum_{i=1}^{n}\left(\left(P_i - \bar{P}\right)^2\right)^{0.5}\right.\right.} \tag{1}$$

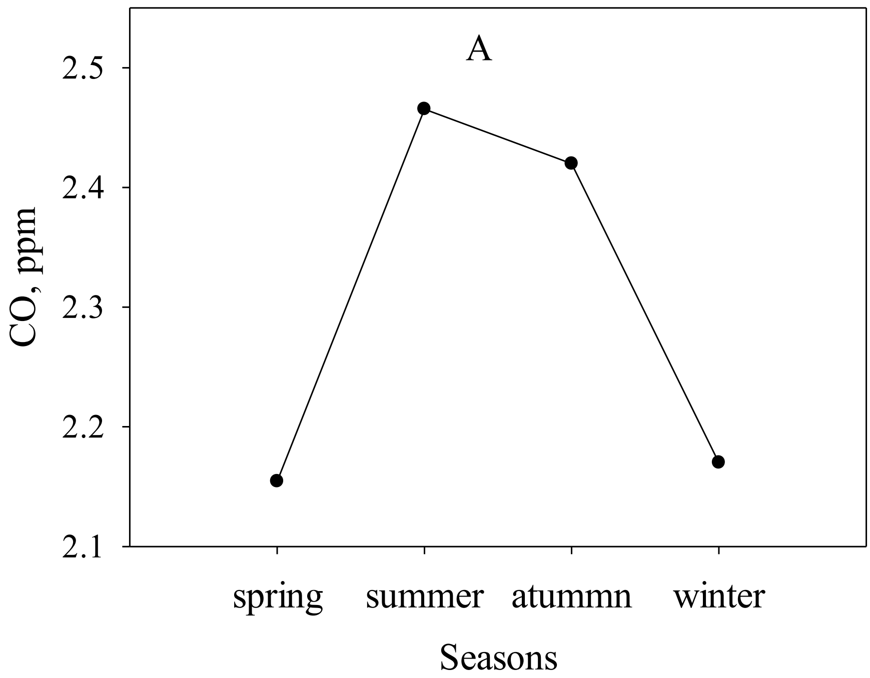
In these equations, O_i is the observed data, P_i is the predicted data, n is the number of observed data, is the average of the predicted data and is the average of observed data [12].

In the present study, to predict the concentration of the pollutants in the next day, firstly the meteorological parameters were used, and secondly, both meteorological data and stability and instability indices were used as input data.

3- Results and Discussion

3.1. Time variations of CO, $PM_{10,}$ and AQI

Seasonal and monthly variations of pollutants concentration are an important factor in determining the ambient concentration of pollutants which may vary due to the pollution composition from one location to the other. Also, the ability of the atmosphere to either absorb or disperse the pollutants is different in terms of latitude, altitude, humidity, and the temperature of a location. Fig.2 (A-C) demonstrates the comparison of the concentration of the pollutants in different seasons. Results showed that the lowest and highest CO concentration had been occurred in summer and winter, respectively; that is compatible with other studies in the world [13]. In winter, natural and human-made pollutants are trapped in the border layers due to frequent temperature inversions (dominant phenomena in Tehran city), while in the warm season this polluted air mixes with the tropospheric air cause dilution of the pollutants. In addition, the lowest and highest concentrations of PM_{10} were in spring and summer. In summer, the dust storm is the most important reason for increased PM_{10} concentration. Other studies in Tehran show that the highest PM_{10} concentration happened in summer [14]. Furthermore, the unhealthy and healthy AQI values are obtained in winter and spring, respectively. Generally, an increase in the concentration of the air pollutants has also been reported in summer which is attributed to low wind speed, high temperature, and subsidence inversion dominating in this season. Monthly variations of CO, $PM_{10,}$ and AQI values for the Sharif air quality monitoring station have been shown in Fig.3 (A-C). The concentration of CO in this monitoring station was the highest in December, November and February which is due to inversion resulting from surface temperatures and increased consumption of fossil fuels and heating tools [13]. Particulate matters in April had the lowest value. Maximum concentrations of PM_{10} occurred in July which is the warmth time in Tehran with much amount of PM_{10}. Enhancement in PM_{10} concentration level is due to reduced wind speed, occurrence of dust phenomenon, decrease of rainfall and not washing-out the particles in the July (summer). The maximum of AQI value was seen in January and December, and the lowest values is in March.



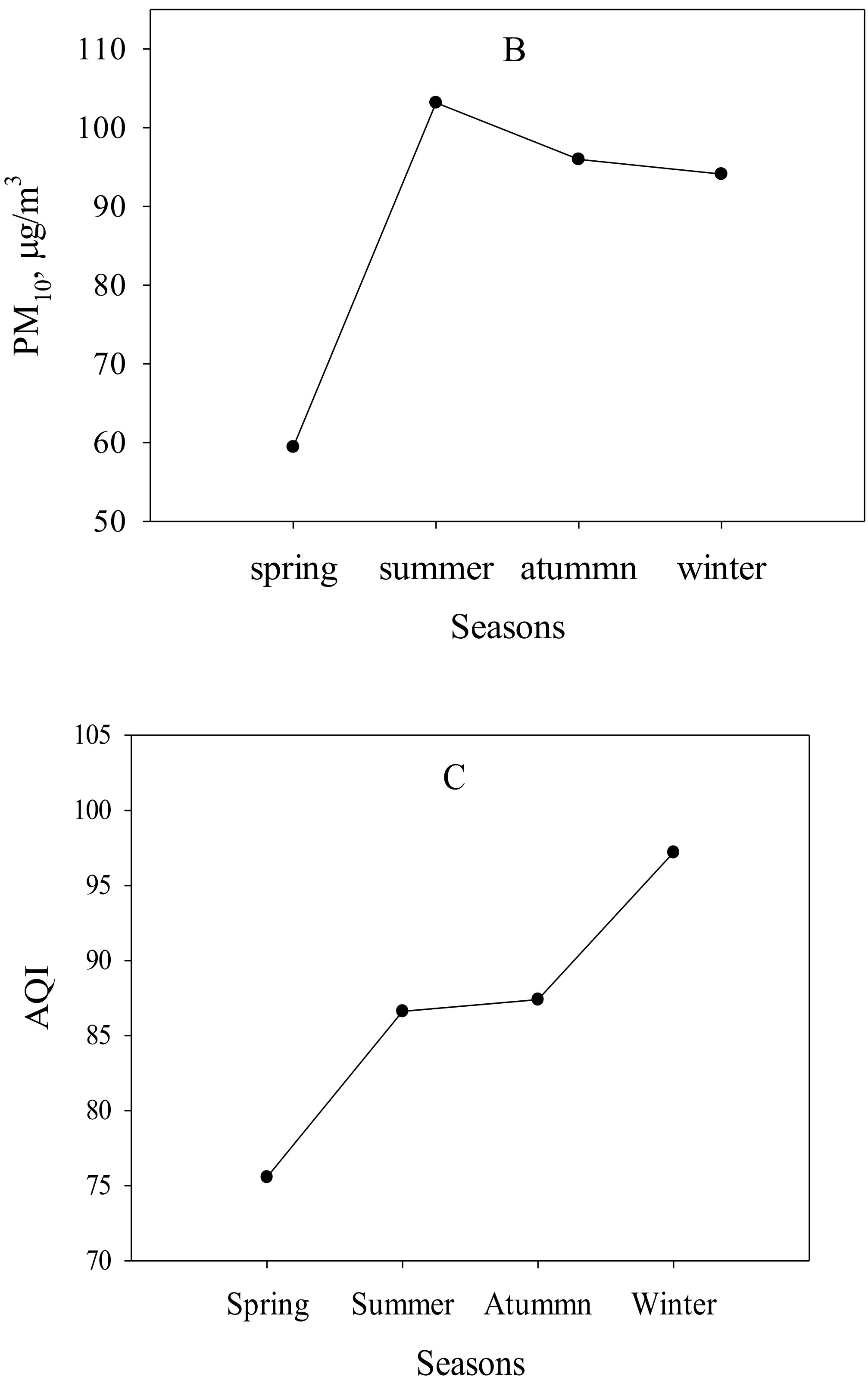
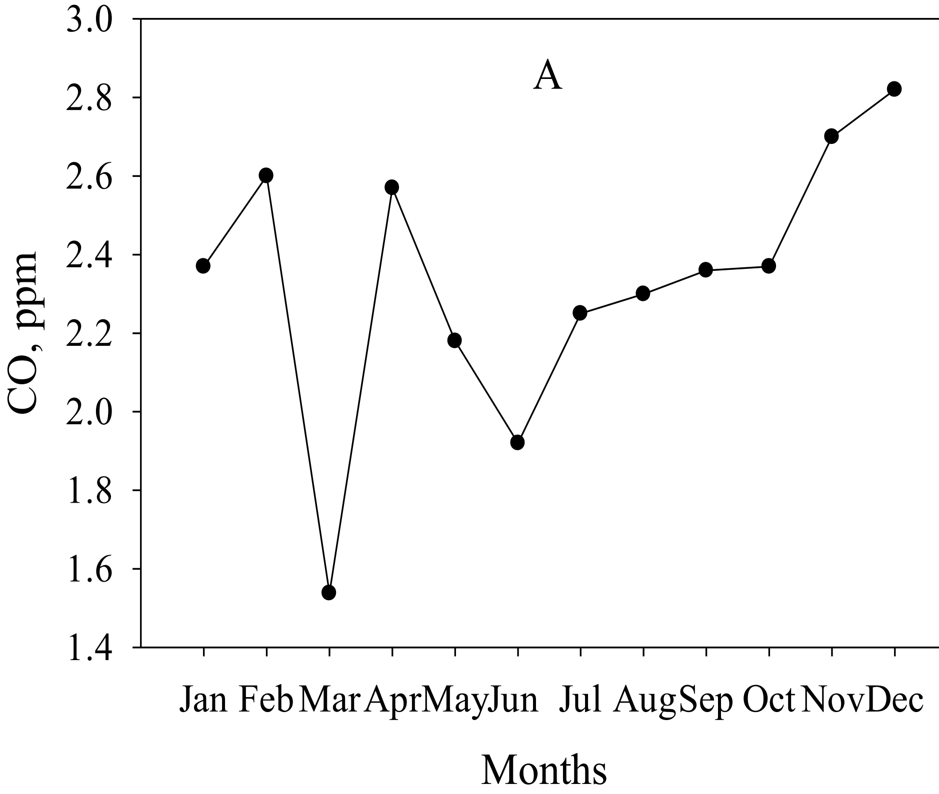
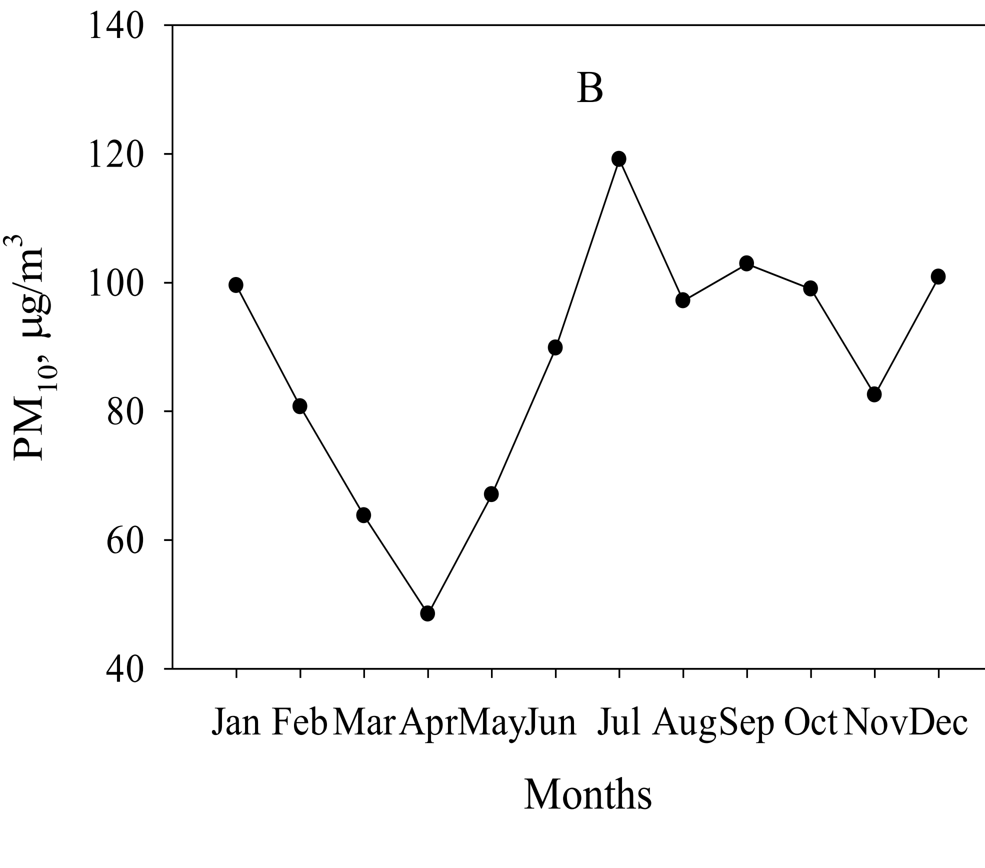


Fig. 2. Seasonal variation of CO (A), PM10 (B), and AQI (C).


A
CO, ppm
3.0
2.8
2.6
2.4
2.2
2.0
1.8
1.6
1.4
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months


B
PM_{10}, µg/m^3
140
120
100
80
60
40
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Months

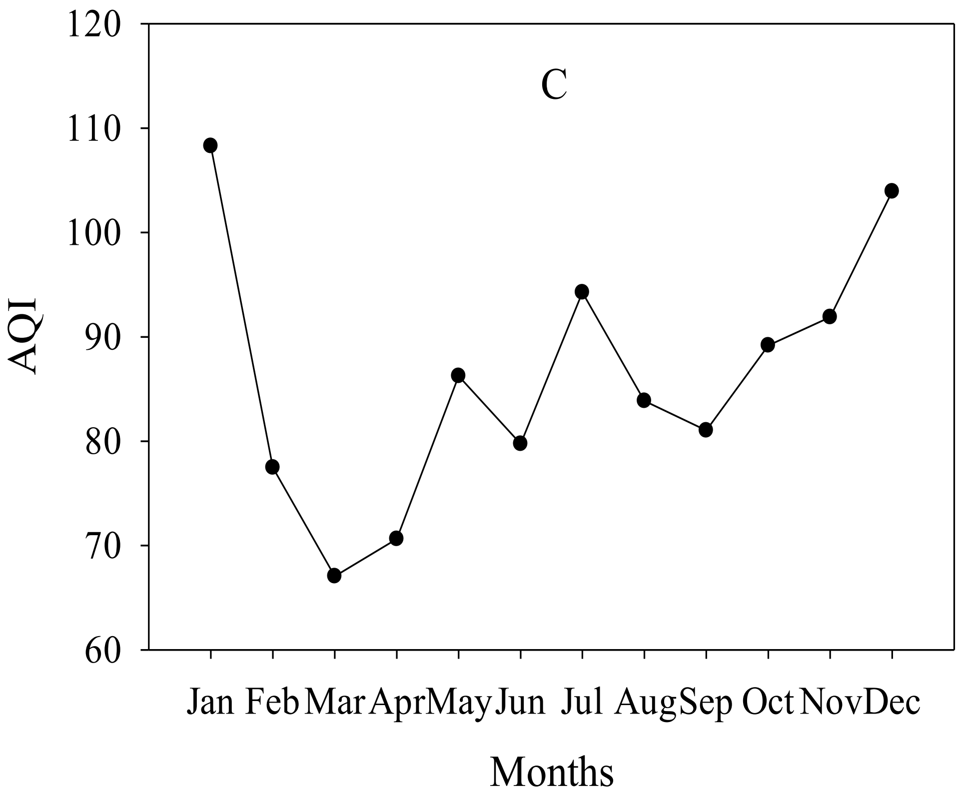


Fig. 3. Monthly variation of CO (A), PM10 (B), and AQI (C).

3.2. Theprediction model with meteorological parameters

The RMSE and correlation coefficient (*R*) for the output model (predicted data), the observed air pollutants concentration, and AQI are shown in Fig.4 (A-C). The correlation coefficients (*R*) between observed and predicted data for PM_{10}, CO, and AQI were 0.76, 0.68, and 0.50, respectively. The range of calculated RMSE for PM_{10}, CO, and AQI was 29.03 to 20.81. In general, the highest correlation coefficient belonged to PM_{10} concentration, which reflects the impact of meteorological factors on the PM_{10} concentration changes during the year. The lowest correlation coefficient with a value of 0.50 was for AQI. Although AQI has fewer correlation coefficients compared to PM_{10}, it is still under the influence of meteorological factors. Some reasons are involved in this prediction such as the fact that air quality is affected by various parameters. Afzali et al., in 2014, investigated the relationship between meteorological parameters and PM_{10} concentration using statistical models that concluded a weak correlation (R=0.18). But, they reported that the use of artificial neural networks significantly improved the fitting of the model with good accuracy (R=0.69) [15]. The meteorological parameters may be classified into two major classes: Those parameters affecting the dispersion of pollutants [16] and those affecting the transformation of pollutants. The main parameters affecting pollutant dispersion are speed and wind direction and atmospheric stability (mixing height, stability class, etc.).

The parameters that affect the pollutants transformation depend on the type of pollutant [17]. For example, the transformation of SO_2 strongly depends on the humidity and temperature of the ambient air to form H_2SO_4 as a secondary pollutant. On the other hand, the formation of tropospheric ozone and peroxy-acetyl-nitrate (PAN) is intensely related to the temperature, UV intensity, and existence of hydrocarbons and NO_2. AQI may be calculated based on the CO or ozone concentration levels. Mckendry showed that the most important meteorological parameters affecting ozone are temperature and wind speed. In contrast, the most important meteorological parameters affecting $PM_{(2.5,\ 10)}$ were rainfall and wind speed. The obtained correlation coefficient between the meteorological parameters and the ozone and PM_{10} (and the ozone) were 0.87 and 0.79, respectively in his study [18]. Duenas et al. concluded that the wind speed and temperature were the most important meteorological factors influencing the variation of ozone levels in a coastal city in Spain with the correlation coefficient of 0.55 and 0.45, respectively [19]they are also used to monitor changes and trends in the sources of both ozone and its precursors. For this purpose, the influence

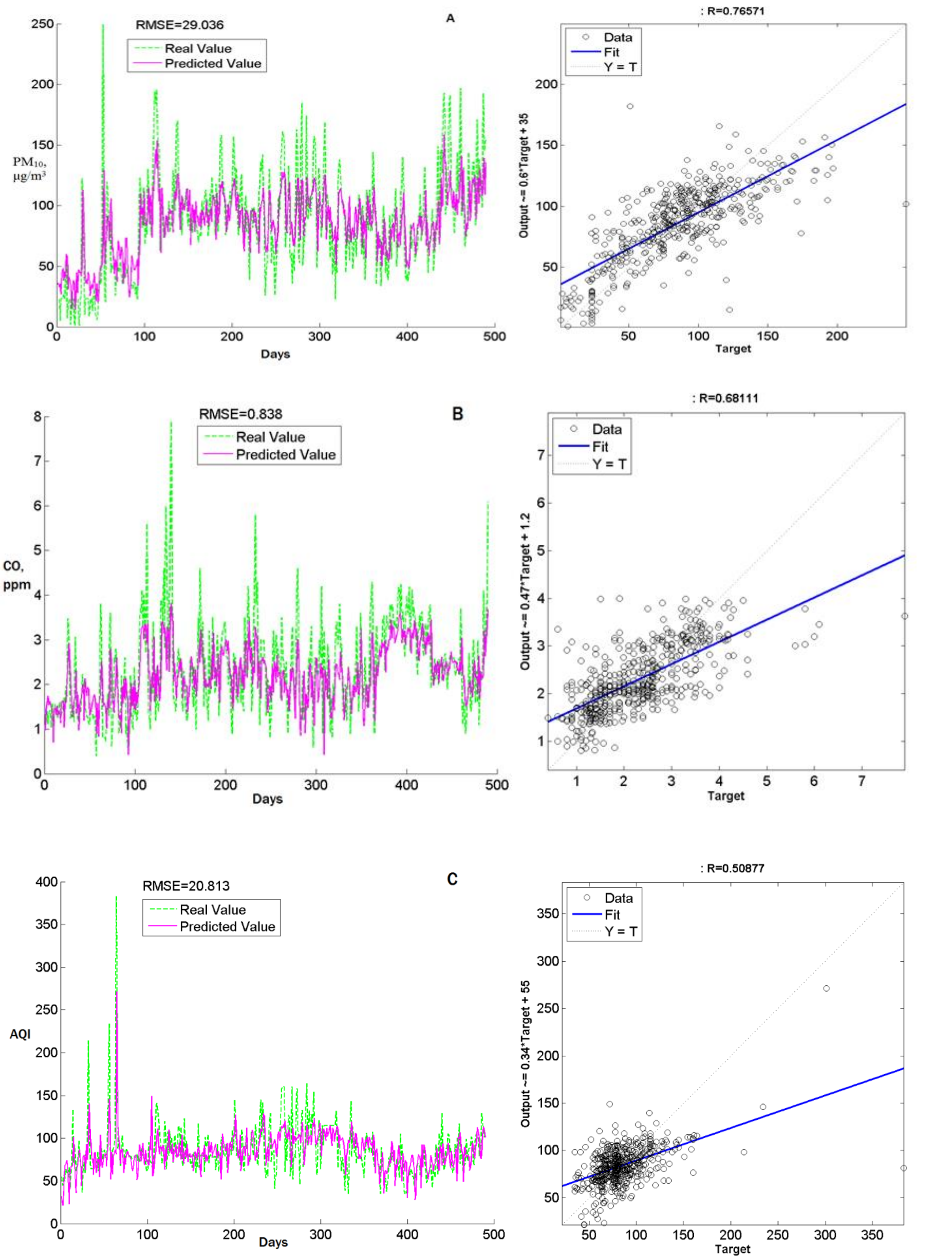


Fig. 4. Correlation coefficient and RMSE for one-day ahead forecasting by meteorological parameters for PM10 (A), CO (B), and AQI (C).

of meteorological variables is a confusing factor. This study presents an analysis of a year of ozone concentrations measured in a coastal Spanish city. Firstly, the aim of this study was to perceive the daily, monthly and seasonal variation patterns of ozone concentrations. Diurnal cycles are presented by season and the fit of the data to a normal distribution is tested. In order to assess ozone behaviour under temperate weather conditions, local meteorological variables (wind direction and speed, temperature, relative humidity, pressure and rainfall. Some literature also reported that in some cases, the statistical models couldn't achieve an acceptable correlation coefficient. Wind speed and temperature inversion, strongly affect the degree of accumulation of pollutants near emission sources such as traffic in urban areas [20]. At low wind speeds, the emitted pollutants tend to accumulate near the source areas. The wind speed increase due to higher ventilation diminishes the pollutants and sweep them. The wind direction affects the air pollutant level when there is a noticeable air pollutant emission source near the receptor point. High temperatures can lead to increased photochemical reactions causing the formation of some secondary pollutants such as ozone and PAN. On the other hand, temperature and UV intensity increase the amount of hydrocarbons emissions. Reyes and Perez concluded that the difference between the maximum and minimum temperatures was the most important factor affecting the prediction of a maximum of 24-h average PM_{10} concentration in Chile, Santiago. Also, they reported that the performance of the multiple-layered perceptron neural network with decreasing error of 63% to 22.2% was better compared to a linear perceptron model with the same inputs [21]. The significant role of ambient temperature in daily, monthly and seasonal concentration of pollutants also has been reported by other authors.

3.3. Prediction model with instability indices

According to worse effects of air pollution, predicting the concentration of air pollutants can be effective in controlling and reducing air pollution programs. Various methods have been used to predict pollutants such as ARIMA, Linear regression, and artificial neural network, but the most desirable model for predicting air pollution is a neural network [23]. According to Fig.5 (A-C) and the output of the model and the actual concentration measurements of PM_{10}, AQI, and CO, the correlation coefficients for PM_{10}, CO, and AQI, were obtained as 0.76, 0.65, and 0.47, respectively. Also, the RMSE values presented by the model in the same order were 28.13, 0.82, and 19.23 respectively. It can be seen that the highest correlation coefficient value belongs to PM_{10}. The lowest correlation coefficient with a value of 0.47 is obtained for AQI. Although the correlation coefficient for AQI takes a minor value it is still under the influence of meteorological factors. The neural network could somewhat predict Tehran's air quality with meteorological parameters and instability indices. To improve the performance of the models, some authors propose using the hybrid forecasting models for the prediction of pollutant concentrations under the conditions that the available valid information maybe not complete [22]. Ping Wang et al. mentioned that ANN or support vector machine (SVM) models and hybrid support vector machine (HSVM) as a hybrid forecasting model has an index of agreement (IA) ranging from 0.92 to 0.96 and a direction accuracy (DA) ranges from 88% to 99% for forecasting process which means the hybrids model can deliver a good prediction result [23].

Nigma et al. by using of artificial neural network model showed that the NN performs well for lag zero forecasting with around 99% accuracy followed by the one-day and two days ahead forecasts with 70-80% and 80-50% accuracy respectively [24]. Shakerkhatibi et al. showed that the ANN model with a good correlation coefficient (R^2= 0.85 to 0.93) could be a reliable model not only for predicting the CO concentrations but also for other contaminants compared to other models such as the EPR model (evolutionary polynomial regression) with correlation coefficient less than 0.41 [25]. Neural network methods have a high ability to simulate the dispersion of air pollutants with proper input data. The error of forecasting which increases for ahead forecast can be improved by amplification and stability of data. The performance of the ANN model is found to be excellent in CO prediction.

4- Conclusions

In the present study, the seasonal and monthly variation in concentrations of PM_{10}, CO, and AQI was investigated. The highest monthly CO concentration was in December due to the increasing fossil fuel consumption, inversion, and utilizations of heating tools. The highest concentrations of CO were in the summer due to the reduced wind blowing and not sweeping of the pollutant to the over boundaries of the city. The highest PM_{10} concentration in July was due to the warmth time, reduced wind speed, and rainfall reduction. Adversely, the highest concentrations occurred in the spring. The highest monthly AQI concentrations were in January and the highest seasonal concentrations were in the spring. Then the prediction of Tehran's air quality for the one day ahead was carried out with a three-layered perceptron neural network with 10 neurons under the performance of sigmoid transmission function and Levenberg Marquardt algorithm using meteorological parameters and instability indices as input data during the years of 2012-2013. For the modeling process once the meteorological parameters only were used as network inputs. In this state, the highest correlation coefficient (R=0.76) and RMSE with a value of 29.03 were related to PM_{10}. In the second step, both meteorological parameters and instability indices were used as network inputs. In the same manner, the highest correlation coefficient (R=0.76) and RMSE with a value of 28.13 were related to PM_{10}. Our results showed that the ability for predicting Tehran's air quality, $PM_{10,}$ and CO concentrations using a multi-layered perceptron neural network could successfully give a reasonable prediction for one day ahead, but to improve the ability of the model comprehensive, data should be gathered in a wide-ranging period.

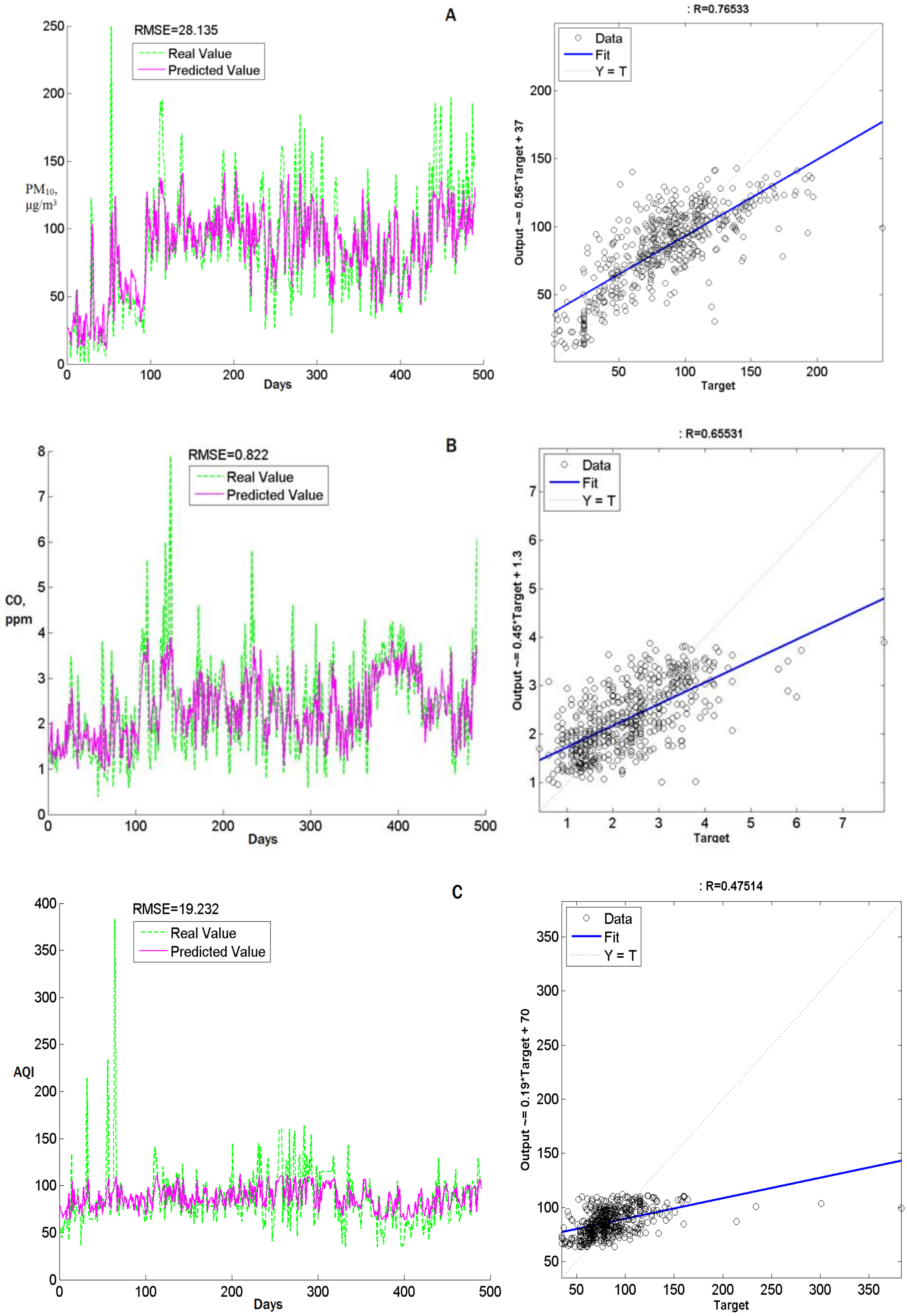


Fig. 5. Correlation coefficient and RMSE for one-day ahead forecasting by meteorological parameters and instability indices PM10 (A), CO (B), and AQI (C).

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