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Forecasting PM_{10} levels using ANN and MLR: A case study for Sakarya City

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Abstract

In this study, potential of neural network to estimate daily mean PM10 concentration levels in Sakarya city, Turkey as a case study was examined to achieve improved prediction ability. The level and distribution of air pollutants in a particular region is associated with changes in meteorological conditions affecting air movements and topographic features. Thus, meteorological variables data for a two-year period for Sakarya city which is located in most industrialized and crowded part of Turkey were selected as input. Neural network models and multiple linear regression models have been statistically evaluated. The results of the study showed that ANN models were accurate enough for prediction of PM_{10} levels.

Keywords: Particulate matter, PM_{10}, prediction, artificial neural network, multi-linear regression

1. Introduction

High air pollution levels cause serious health problems. Particulate matter (PM) is one of the most harmful air pollutants in the form of dust, soot, dirt, smoke and liquid droplets in the ambient air. The main source of PM emissions is fossil fuel consumption in vehicles, power plants and industrial processes. These particles can remain suspended in the air for a long time and can escape being cleaned by rain. Due to their small size, these particles present high health risks. According to various recent epidemiological investigations, particulate matter (PM) can seriously affect the health of living things even at relatively low levels in the atmosphere. Pulmonary and cardiovascular diseases such as chronic respiratory problems, eye irritation, shortness of breath and cancer are some of the important and serious health problems caused by PM (Feng *et al.*, 2015; Bai *et al.*, 2016; Evagelopoulos *et al.*, 2006; Ghozikali *et al.*, 2016).

PM10, aerodynamic particles with a diameter less than 10µm, has an important place among such particles. A restriction at the level of PM_{10}, which should not be exceeded in order to reduce the adverse effects of PM_{10} on air quality and human health, has been determined by the European air (2008/50/EC) directive. According to this directive, the European Union (EU) has set air quality standards for the PM10 as the annual average limit value (40 g/ml) and the 24 h concentration limit (50 g/m^3). For this reason, it is very important to assess and monitor the PM levels by using a forecasting model to promote the adverse conditions to improve air quality (Caselli *et al.*, 2009; Özdemir and Taner, 2014). Estimation of particulate matter levels through modeling of all relevant dynamic, physical and chemical processes requires a detailed examination of a large number of parameters (Gupta and Mohan, 2013; Özdemir and Taner, 2014). If the factors affecting the sources and levels of particulate material are adequately characterized and quantified, these limits can be effectively controlled.

Artificial Neural Networks (ANN) is one of the widely applied artificial intelligence models in different research areas for prediction (Elangasinghe *et al.,* 2014; Russo *et al.,* 2015; Fang and Wang 2017; Biancofiore *et al.* 2017; Özgür and Tosun 2017; Altıner and Kuvvetli, 2017; Sofuoglu *et al.* 2006). ANN models have approved to be convenient way for estimation air pollutants in cities, especially where monitoring networks are used to measure concentrations of pollutants and meteorological variables (Fang and Wang, 2017; Sofuoglu *et al.,* 2006; Özgür and Tosun, 2017). One of the main characteristics of these systems is learning and generalization capacity based on real examples (Mishra *et al.*, 2016). The network learns the definition of the relationship between the given input sequence and its corresponding output. After learning, when the network is presented with a new input, it can provide output based on the established functional relationship. In the literature, there are statistical and mathematical studies have been carried out to evaluate the relationship between PM_{10} concentration levels and meteorological factors.

Recent studies have shown that the performance of ANN estimates better than statistical linear methods because pollution-air associations often have complex and non-linear properties (Gardner and Dorling, 1998)(Blanes-Vidal, Cantuaria and Nadimi, 2017; Zafra, Ángel and Torres, 2017; Prasad, Gorai and Goyal, 2016). However, ANN models vary according to the current situation and each model must be trained for each specific city with weather conditions, pollutant emissions, traffic information, day of the week, history, cloud cover, etc. (Taşpinar, 2015; Russo *et al.,* 2015; Mishra, Goyal and Upadhyay, 2015b; Guadalupe *et al.,* 2015; Elangasinghe *et al.,* 2014; Özdemir and Taner, 2014; Caselli *et al.,* 2009; Moazami *et al.,* 2016; Bai *et al.,* 2016). Perez and Reyes, (2006), established a neural network to estimate level of average PM10 concentration on the next day in Santiago, Chile. They reported better prediction ability for multilayer neural network then linear model. Kukkonen *et al.,* (2003) performed comparative study with five neural network (NN) models, a linear statistical model and a deterministic modeling system to predict NO_2 and PM_{10} concentrations using data obtained from two stations in central Helsinki for the year of 1996–1999. They concluded that the non-linear NN models performed slightly better than both deterministic and linear statistical models. Hooyberghs *et al.* (2015) investigated the design of a neural network tool to forecast the daily average PM_{10} concentrations in Belgium one day ahead. Brunelli *et al.,* (2007) formed a recurrent neural network based forecaster to predict daily maximum concentrations of various air pollutants including PM10 in Palermo, Italy. Caselli *et al.,* (2009) compared two support decision systems (neural networks and a multivariate regression model) using meteorological parameters to predict daily PM10 concentrations 1, 2 and 3 days in advance in Bari, Italy. Gennaro *et al.,* (2013) developed and tested an artificial neural network (ANN) to forecast PM10 daily concentration at the Montseny and Barcelona (Spain) sites. The hourly PM10 concentrations, and meteorological data such as wind speed, wind direction, rain, solar radiation, temperature, relative humidity and air masses origin was used for predicting 24-h average PM10 concentrations 1-day in advance. Özdemir and Taner, (2014) investigated the possible effects of different meteorological factors on air pollution caused by PM_{10} in two different regions (urban and industrial) in Kocaeli, Turkey. For this purpose, they applied and compared multi-linear regression (MLR) and artificial neural networks (ANN) using different meteorological factors (temperature, relative humidity, air pressure, wind speed, and direction) on PM_{10}. Hur *et al.,* (2016) developed a neural network model for predicting PM_{10} grades using synoptic patterns of meteorological fields to ensure a statistical reference for the current Korean Ministry of Environment (KME) PM_{10} forecasting system. Bai *et al.,* (2016) developed and tested back propagation neural network (BPNN) by wavelet decomposition to forecast daily air pollutants (PM_{10}, SO_2, and NO_2) concentrations in Nanan District of Chongqing, China. Daily meteorological data i.e. wind speed temperature, atmospheric pressure, relative humidity, visibility, precipitation, and illumination, used as input parameters.

As stated in literature, neural networks have benefits such as accuracy and fast response when employed for estimating air pollutant levels. Especially, when a theoretical approach cannot be applied, ANNs has the capability to simulate nonlinear functions. ANN models can take into account a large number of variables and analysis takes less time. The main goals of the present study are to investigate the relationships between PM_{10} levels and meteorological and time dependent variables, to decide on those which can be used for prediction and obtain an improved prediction. In this study, we analysed continuous measurements of PM10 concentration and meteorological parameters during a time period between dates 1/1/2015 and 15/10/2016 for one of the most industrialized city of Turkey, Sakarya city which has critical PM10 levels for the first time. A multi linear regression and neural network approach has been applied to predict PM10 concentrations for one day ahead, using meteorological variables and were compared. The results of the study can help decision makers to get necessary precautions and carry out efficient environmental management.

2. Materials and Methods

2.1. Dataset

Turkey's PM10 standard for the 24 h average is 50 µg/m^3, and when this average exceeds 80 µg/m^3, restrictions to emissions apply. The level of PM10 allowed in Turkey for year 2015 is an annual average of 56 µg/m^3. Based on this criterion, only 43 of 81 cities (53%) are below of this limit. On the other hand, when the EU air quality limit (40 µg/m^3) is compared; 62 of 81 cities (77%) are observed to have air pollution above the normal allowed limit. In addition to this, when the WHO air quality limit (20 µg/m^3) is considered and evaluated, only one city (Çankırı) has air quality below the normal permissible limit.

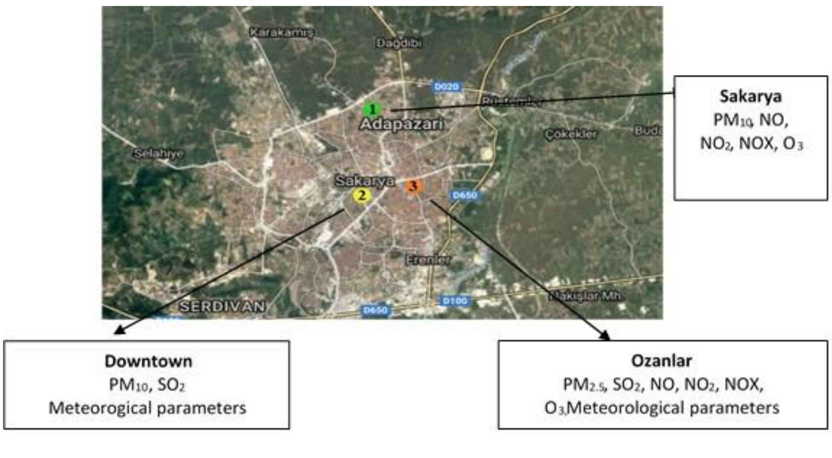
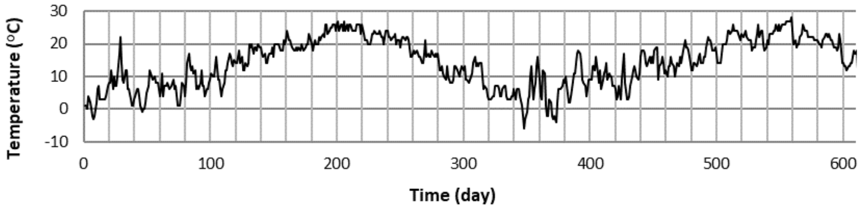


Figure 1. Location of PM10 monitoring stations in the city of Sakarya, Turkey



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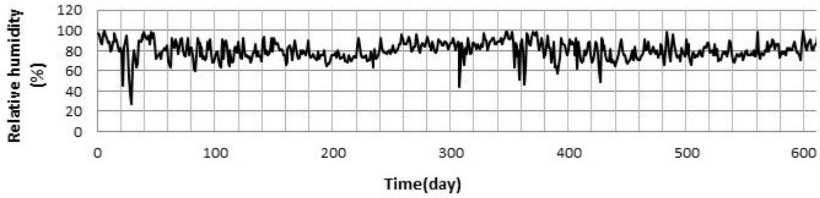

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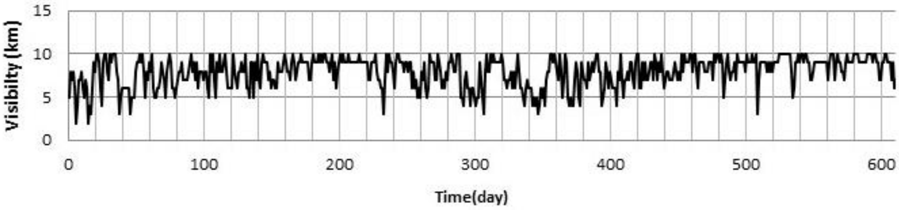

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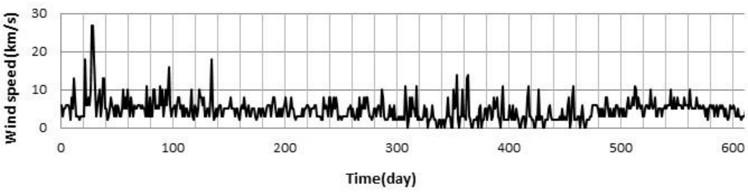

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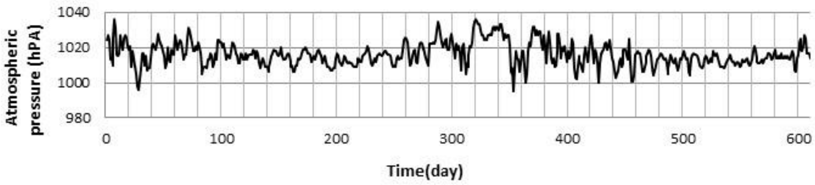

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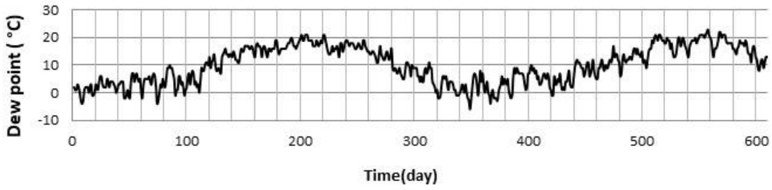

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Figure 2. Meteorological data from 1/1/2015 to 15/10/2016

Sakarya (between latitude of 30°53'North and longitude of 29°57'East) is in the Marmara region of Turkey, which is the most industrialized and crowded part of country. Furthermore, Sakarya is located on the main highways and railroads connecting the Marmara region with other regions of country. It has an approximate population of 269.079 inhabitants. Many local factors have resulted in an increase of PM10 in the last years: the population growth, the car traffic increase, the local industry, including thermoelectric power plants, the emissions produced by agriculture, as well as the topography and the climatic characteristics. Currently, according to the reports of Republic of Turkey Ministry of Environment and Urbanization, Sakarya is ranked as one of the most polluted cities in Turkey.

Fig. 1 shows the three air quality monitoring stations located in different parts of Sakarya. These stations are called as Sakarya-UHKIA, Downtown and Ozanlar. Ozanlar is close to several main roads, including one of busiest national highway so that the site is highly exposed to pollutants due to transportation. Also, the Ozanlar region is located in the industrial zone of the Sakarya city. For this reason, this region is an area where the highest concentrations of pollutants are measured. Thus, it is thought that Ozanlar region represent the worst pollution scenario for the city of Sakarya.

Thus, in this study, the forecasting models have been developed and analyzed for Ozanlar data. The aim in this study is to forecast hourly concentrations of PM10 in Ozanlar station. The measured meteorological variables between dates 1/1/2015 and 15/10/2016 are: wind direction, wind speed, temperature, relative humidity, atmospheric pressure, precipitation and solar radiation (Fig.2).

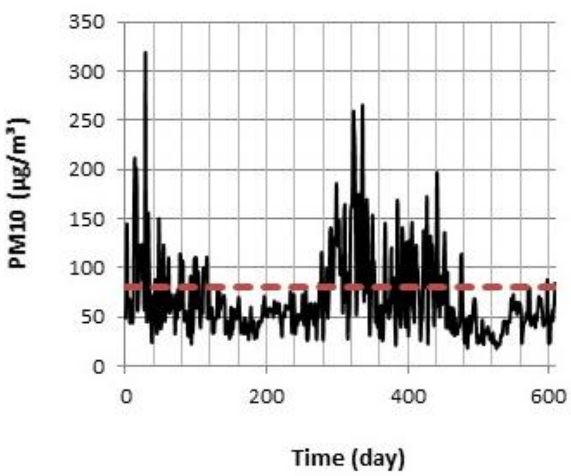


Figure 3. PM10 concentration for the period 1/1/2015 - 15/10/2016. The fluctuation indicates daily (24-h mean value) records of PM10 concentration, and the horizontal line refers to the daily legal limit value (80 μg/m³).

Since the transport and distribution of atmospheric air pollutants can be affected by regional weather conditions, meteorological parameters play an important role in the pollutant distribution affecting ground level concentrations. Fig. 3 shows the time dependent variation of PM_{10} levels between dates 1/1/2015 and 15/10/2016. Peak values are related with winter season when fossil fuel consumption increases for house heating. Daily data (24-h mean value) of PM_{10} concentration in Sakarya, Turkey for the period 1/1/2015 - 15/10/2016, was provided by Turkish Ministry of Environment and Urbanization (National Air Quality Observation Network).

2.2. Multiple Linear Regression (MLR)

MLR method represents a function of a number of certain parameters that includes one output variable to be predicted and two or more independent variables used as inputs. MLR is based on least squares; it expresses the value of the predicted parameter as a linear function of one or more predictor parameters: In general, MLR can be defined as in Eq.1;

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 +....+b_nX_n + \varepsilon \quad (1)$$

where Y is the dependent variable, X_1, X_2…,Xn are the independent variables, b_1, b_2…,b_n are linear regression constants. In this work, PM10 is the dependent variable meteorological variables are independent variables which are used for prediction and ε is the error term.

2.3. ANN Model

ANNs are actually computing systems that are inspired from biological neural networks. Among the various ANN species, Multilayer Perception Neural Network (MLPNN) is one of the widely applied ANN construct. MLPNN generally are consists of input, output, and hidden layers. Each layer composed of basic elements called a neuron or a node. The nodes are interconnected and the synapses are characterized by a weight factor that indicates the connection between the two nodes. Each node receives input values, processes them and passes them to the next layer.

This is done using weights and uses its own transfer function to create an output value (Bai *et al.*, 2016a; Moazami et. al., 2016). MLPNNs are trained in input data using an error diffusion back propagation algorithm, one of the most popular algorithms. The first step is forward, passing to the network to access the input output layer and calculate the output value. After the error calculation, the error of the weights assigned to the start of the second step backwards through the network input layer begins to correct so as to minimize (Emamgholizadeh *et al.,* 2014). This represents a complete cycle known as a period in which all data pass over the network. 'Feed forward' means that a node has only one node in the output layer. Nodes in one layer are linked and there are no lateral or feedback connections. MLPNN employs BP algorithm which is sensitive to a randomly assigned initial connection weight (Csábrági *et al.,* 2017; Bai *et al.,* 2016). In this study, the Levenberg-Marquardt algorithm was used to adjust the MLPNN weights and the number of epochs applied was 1000. There are various transfer functions used for predicting outcomes. In this research, we have used commonly applied log-sigmoid, tangent sigmoid and purelin functions. The expressions for log-sigmoid and tangent sigmoid functions are given in Eq. 2 and Eq. 3.

$$y(x)=\frac{1}{1+e^{-ax}} \tag{2}$$

$$y(x)=\frac{2}{1+e^{-ax}}-1 \tag{3}$$

In these equations "x" represents input of transfer function and "a" is the slope of parameter and y is the output. A set of actual data consisting of 602 data sets obtained from database were used for training (70%), validation (15%), and testing (15%) the neural networks. The input layer included six neurons: temperature, atmospheric pressure, wind speed, relative humidity, visibility and dew point. All dataset were normalized to obtain similar impact of all inputs in ANN models. The normalization equation can be given as in Eq. 4.

$$NI_{ij}=\frac{I_{(i,j)}-\min(j)}{\max(j)-\min(j)} \tag{4}$$

In Eq. 4, *I* represents the input value, *NI* is the standardized value, *i* is the number of patterns and j indicates the measured value of variables (Keskin and Terzi, 2006). As, more hidden layers may cause over fitting and the model cannot adapt to new inputs, single hidden layer network was subjected for further study to determine the network parameters. One hidden layer and a hyperbolic tangent sigmoid transfer function were used between the input and the hidden layers, and a linear transfer function was applied between the hidden and output layers. Neural Network Toolbox of MATLAB was used for ANN calculations.

2.4. Evaluation of Prediction Performance

The performance of constructed ANN models were statistically measured, in terms of the mean square error (*RMSE*), mean absolute error *(MAE)* and coefficient of determination (R^2) as given in Eq.5-7, respectively:

$$RMSE=\frac{1}{n}\sum_{i=1}^{n}\left(Y_{pi}-Y_{di}\right)^2 \tag{5}$$

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|Y_{pi}-Y_{di}\right| \tag{6}$$

$$R^2=1-\left(\frac{\sum_{i=1}^{n}\left(Y_{pi}-Y_{di}\right)^2}{\sum_{i=1}^{n}\left(Y_{pi}-\bar{Y}\right)^2}\right) \tag{7}$$

where, N is the number of data, Y_{pi} is the predicted value from observation i, Y_{di} is the real value from observation i, and $\bar{Y}$ is the average of the real value. The coefficient of determination (R^2) is a number that indicates how well data fit into a statistical model such as a regression line or curve. The RMSE is used to measure the error rate of a regression model and it represents the standard deviation of the model prediction error. The model is considered accurate when R^2 is close to 1.0, while *RMSE* must be as small as possible. MAE is a measure used to evaluate how close the estimates are to the observed (real) results. The acceptable values of *RMSE, MAE* and R^2 mean that the model is able to describe the actual behavior of system.

3. Results and Discussion

3.1. Prediction using Multivariate Linear Regression

To predict the PM_{10} values, multiple linear regression models were investigated at first. Temperature (T), dew point (D), relative humidity (H), pressure (P), visibility distance (VD) and wind velocity(WV) were selected as prediction parameters from the dataset obtained from Ozanlar station. The model equation MLR_1 was established by these six selected parameters and it is given in Eq. 5. The statistical analysis was found to be insignificant (p-value greater than 0.05) for relative humidity (H) in this first model. For this reason, another model, denoted as MLR_2, is derived without the H parameter.

MLR_2 is shown in Eq.8. The constants and statistical analysis results of both models are shown in Table 1.

Table 1. Coefficients and statistical results for MLR analysis

	First Case			**Second case**		
	Coefficient	**SE Coef.**	**p-Value**	**Coefficient**	**SE Coef.**	**p-Value**
Constant	-803.71	251.91	0.001	-802.20	251.00	0.001
T	4.81	1.15	0.000	5.06	0.58	0.000
D	-6.57	1.20	0.000	-6.82	0.60	0.000
H	-0.09	0.36	0.805			
P	0.91	0.25	0.000	0.90	0.25	0.000
VD	-5.45	1.01	0.000	-5.33	0.87	0.000
WV	-1.94	0.49	0.000	-1.90	0.47	0.000

$$MLR_1=-803.71+4.81*T-6.57*D-0.09*H+0.91*P-5.45*VD-1.94*WV \tag{8}$$

$$MLR_2=-802.20+5.06*T-6.82*D+0.90*P-5.33*VD-1.90*WV \tag{9}$$

The standard deviation of the estimate of a regression coefficient measures how accurately the coefficient of the model predicts the unknown. As seen in Table 1, although the standard deviations of the coefficients for MLR_2 are relatively low, the R^2 value is not sufficient for prediction. The PM10 data estimated by model equality MLR_2 were compared with the observed PM_{10} data and the results are shown in Fig. 4.

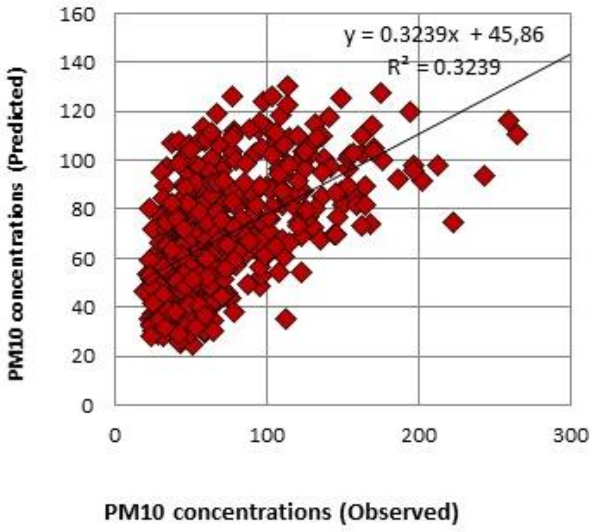


Figure 4. Comparison of observed PM_{10} concentrations versus predicted values using MLR_2

3.2. Prediction Using ANN

In order to obtain the optimum performance, different pairs of transfer functions for the hidden layer and output layer with different adaption learning function were tested, varying the neuron number of the hidden layer. Transfer functions calculate a layer's output from its net input. Different combinations of tangent sigmoid (tansig) and linear (purelin) transfer functions were tested to determine the best combination that will yield good results. Moreover, learning functions are mathematical procedures can be applied to adjust weights and biases of a network. We have used LEARNGD and LEARNGDM.

LEARNGD is the gradient descent weight and bias learning function and LEARNGDM is the gradient descent with momentum weight and bias learning function. The training performance results of different ANNs structures with LM was shown in Table 2. Among transfer functions, logsigmoid function was failed to predict PM_{10} levels in acceptable limits. Due to low correlation coefficients (R^2<0.2), results of functions including logsigmoid are not included in Table 2.

As seen from Table 2, ANN_7 network performs better than the other models according to statistical analysis results with lowest MAE and RMSE and highest R^2 values. The ANN_7 structure included 6 input parameters, namely temperature, visibility distance, dew point, wind velocity, pressure and relative humidity with 12 neurons in hidden layer and 1 output parameter-PM10 concentration. The best MLP model prediction was obtained with learning function LEARNGDM, and the transfer function pair Tansig-Tansig, generating 6-12-1 MLP structure. The RMSE, MAE and R^2 values for ANN_7 model was 15.700, 9.047 and 0.840 respectively. Based on this optimal result, a simulation of the ANN_7 model performance was carried out and shown in Fig. 5.

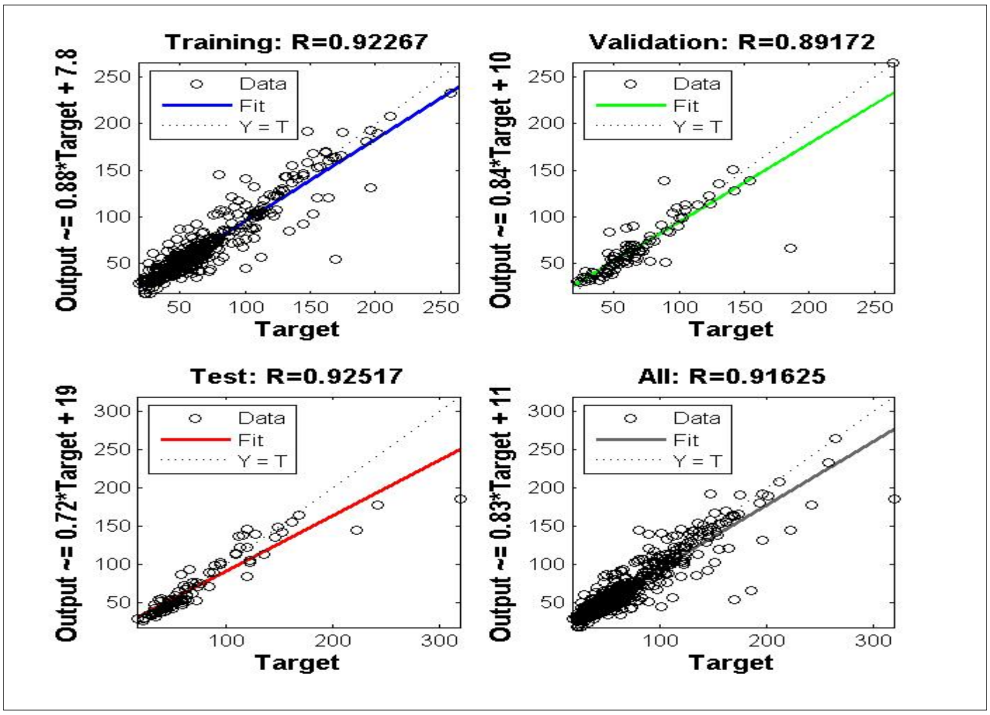
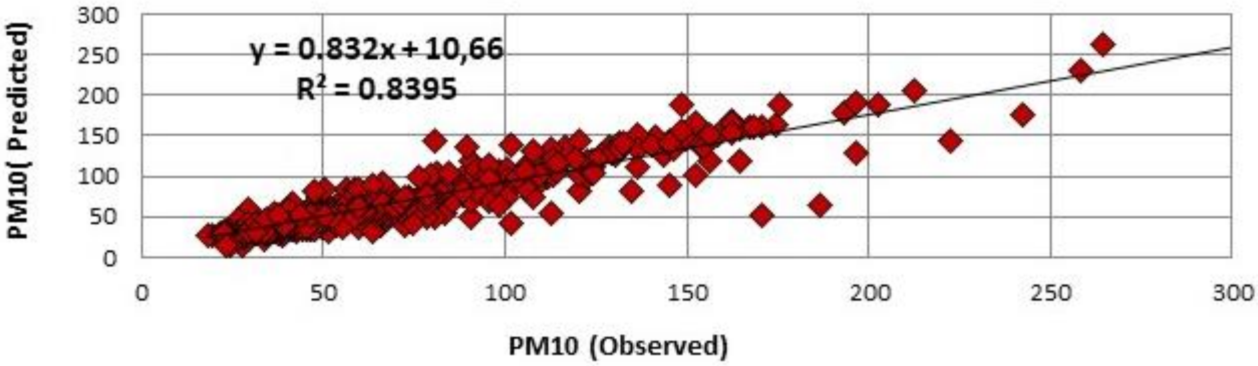
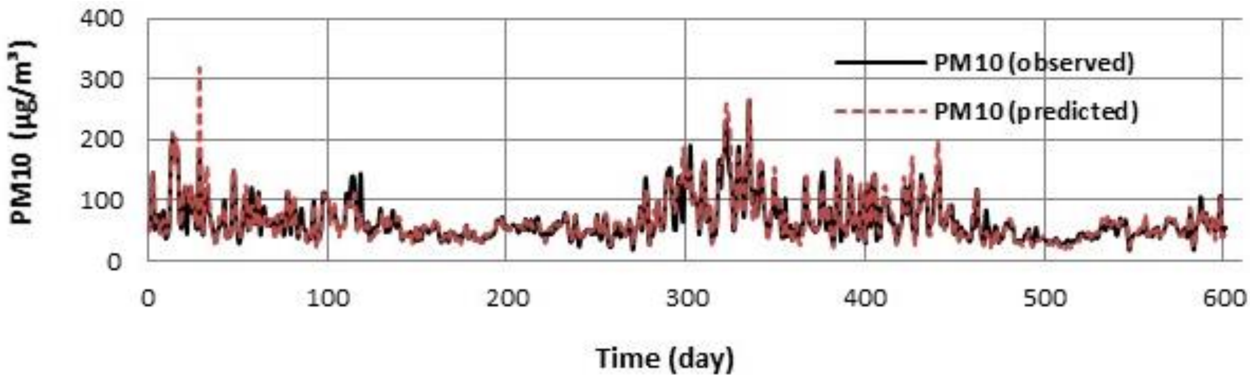


Figure 5. ANN_7 model output

As shown in Fig. 5, the training of the selected model was successful; the R was found to be equal to 0.89172 and 0.92517 for validation and testing, respectively. Thus, it is concluded that ANN_7 network is more suitable for estimating the PM_{10} concentration. According to Fig. 6a, which is the predicted PM_{10} concentration and the observed PM_{10} concentration correlation diagram, the correlation coefficient based on the results was approximately 0.8395 which is highly accurate. According to the shown diagram in Fig. 6b, it can be observed that there is a strong correlation between observed values and predicted ones. The results of the study were comparable with previously reported on prediction of various pollutant concentrations (Srimuruganandam and Shiva Nagendra 2010; Biancofiore *et al.* 2017; Ozel and Cakmakyapan 2015; Auder *et al.* 2016b) . Although its non-linear and complex structure, multiple linear regression models assume a linear relationship between meteorological variables and PM_{10} concentration. This is why the results obtained with the linear regression model are less accurate than those obtained with the ANN models.



(a)



(b)

Figure 6. a) Observed PM_{10} concentrations versus predicted values b) Correlation between observed values and predicted ones

Table 2. The comparisons performance of different ANN structure

Model	Adaptain learning function	Transfer function	Number of hidden neurons	RMSE	MAE	R^2	Model	Adaptain learning function	Transfer function	Number of hidden neurons	RMSE	MAE	R^2
ANN_1	Learngdm	Tansig-Tansig	10	19.327	12.668	0.757	ANN_{19}	Learngdm	Tansig-Tansig	16	19.435	11.619	0.754
ANN_2	Learngdm	Tansig-Purelin	10	17.661	10.473	0.799	ANN_{20}	Learngdm	Tansig-Purelin	16	17.661	10.203	0.805
ANN_3	Learngdm	Purelin-Purelin	10	23.313	14.907	0.652	ANN_{21}	Learngdm	Purelin-Purelin	16	23.356	14.706	0.646
ANN_4	Learngd	Tansig-Tansig	10	20.453	12.604	0.730	ANN_{22}	Learngd	Tansig-Tansig	16	17.585	12.437	0.803
ANN_5	Learngd	Tansig-Purelin	10	20.962	13.035	0.714	ANN_{23}	Learngd	Tansig-Purelin	16	17.106	11.233	0.809
ANN_6	Learngd	Purelin-Purelin	10	23.076	14.966	0.653	ANN_{24}	Learngd	Purelin-Purelin	16	23.241	15.039	0.649
ANN_7	**Learngdm**	**Tansig-Tansig**	**12**	**15.700**	**9.047**	**0.840**	ANN_{25}	Learngdm	Tansig-Tansig	18	16.756	11.466	0.818
ANN_8	Learngdm	Tansig-Purelin	12	22.883	15.298	0.659	ANN_{26}	Learngdm	Tansig-Purelin	18	19.618	12.319	0.749
ANN_9	Learngdm	Purelin-Purelin	12	23.175	14.832	0.650	ANN_{27}	Learngdm	Purelin-Purelin	18	23.562	14.830	0.638
ANN_{10}	Learngd	Tansig-Tansig	12	21.458	12.749	0.709	ANN_{28}	Learngd	Tansig-Tansig	18	17.860	11.004	0.794
ANN_{11}	Learngd	Tansig-Purelin	12	19.372	11.801	0.763	ANN_{29}	Learngd	Tansig-Purelin	18	16.725	11.599	0.818
ANN_{12}	Learngd	Purelin-Purelin	12	23.115	14.848	0.651	ANN_{30}	Learngd	Purelin-Purelin	18	23.187	15.190	0.650
ANN_{13}	Learngdm	Tansig-Tansig	14	19.141	11.274	0.767	ANN_{31}	Learngdm	Tansig-Tansig	20	19.031	11.315	0.771
ANN_{14}	Learngdm	Tansig-Purelin	14	17.166	10.253	0.813	ANN_{32}	Learngdm	Tansig-Purelin	20	20.348	12.267	0.732
ANN_{15}	Learngdm	Purelin-Purelin	14	23.284	15.377	0.647	ANN_{33}	Learngdm	Purelin-Purelin	20	23.165	14.904	0.650
ANN_{16}	Learngd	Tansig-Tansig	14	19.155	13.948	0.766	ANN_{34}	Learngd	Tansig-Tansig	20	19.895	11.656	0.746
ANN_{17}	Learngd	Tansig-Purelin	14	16.989	11.202	0.813	ANN_{35}	Learngd	Tansig-Purelin	20	17.639	11.203	0.801
ANN_{18}	Learngd	Purelin-Purelin	14	23.299	15.107	0646	ANN_{36}	Learngd	Purelin-Purelin	20	23.195	15.118	0.649

4. Conclusion

In this study, Sakarya city which is located in most industrialized and crowded part of Turkey with critical PM_{10} levels was selected as a case study for developing prediction models for PM10 levels. The models used to predict PM10 air pollutant concentrations should be established taking into account the meteorological and topographical characteristics. Thus, wind speed, temperature, dew point, relative humidity, visibility and sea level pressure were used to estimate the daily average amount of PM_{10} concentration. ANN and MLR models were employed to daily PM10 and metrological data to predict one day ahead PM10 concentrations. MLR models showed lower R^2 values and were evaluated as inadequate for PM10 prediction. 36 different ANN model structures were established and trained. Feasibility of 36 different ANN models with various network structures using tangential and logistic sigmoid hidden layer transfer functions with linear output layers were investigated.

Model performance was tested depending on root mean squared error (RMSE), mean absolute error (MAE), and correlation coefficients (R^2) between estimated and compared with actual PM10 values.

The results showed that the predictions made with artificial neural networks showed better results than MLR and thus thought as more efficient way for a prediction approach. The ANN_7 model showed lower RMSE and MAE and higher R^2 values when compared with other models and selected as best model. This is the first study on PM10 level prediction in Sakarya city and results of ANN prediction was comparable with previous studies for other cities. Moreover, the results are considered to be more reliable since the level of pollutants in the installation of the models is not used as input, unlike general trend in previous studies. The results of the study could be used to support improvements in environmental management policies and enable application of sustainable development strategies.

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