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Neural Network Forecast for Daily Average PM_{10} Concentrations

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Over the past years, the health impact of particulate matter (PM) has become a very current subject. In the environmental sciences a lot of research effort goes towards the understanding of the particulate matter phenomenon and the ability to forecast particulate matter concentrations. The aim of the present work is to evaluate the potential of various developed artificial neural network models to provide reliable predictions of PM_{10} concentrations in Kayseri. Model structure obtained from air quality monitoring network system performed by the Ministry of Environment and Forestry was developed for 18 month data of Kayseri and the structure was refined by Levenberg-Marquardt algorithm. Performance results of artificial neural network models was compared with multiple regression analysis and neural network give better predictions than multivariate regression models.

Key Words: PM_{10}, Ambient air, Air pollution forecast, Neural network model, Erciyes University.

INTRODUCTION

The adverse effects of airborne ambient particulate matter have become a well-recognized problem in environmental sciences. Besides the reduction of visibility and the deposition of trace elements, the direct impact on human health *via* inhalation is an important issue. The combination of PM_{10} one of the significant air polluters, contains more than one air pollutants among which are aerosol, smoke, soot, combustibles, dust, sea salt and pollens. In several studies reveal the direct effect of PM_{10} concentration on human health[1-3]. Artificial neural networks models which are the products of real brain functions offered quite successful results in predicting widely-available air pollutants and different studies concentrations[4-8]. Besides, several studies proved that compared to traditional statistical models, artificial neural network models are far more excellent[9-11]. Lately PM_{10} concentration too could be successfully predicated *via* ANN models[12-18]. In this paper, we describe the design of a multi-layer ANN model forecasting tool for the ambient PM_{10} concentrations in Kayseri.

Overview of artificial neural network: Multi-layer ANN, the most frequently chosen and practiced model in engineering, are dense parallel systems composed of various process elements which are attached to each other *via* weights. The most widely used one amongst ANN methods is the one that works according to the principle of error back-propagation Lipmann[19]. Fig. 1 illustrates the structure of the three-layer artificial neural network used in this study.

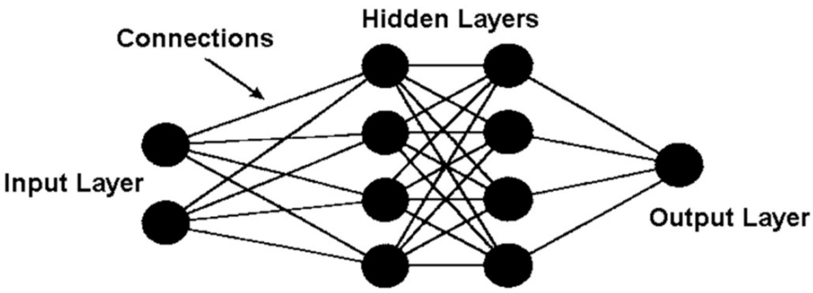


Fig. 1. A simple multi-layer ANN model

Data are transferred from one layer to another *via* several series processes. Input layer contains input parameters of process or system; hidden layer however enables evaluating input parameters by selected model algorithm and transferring it to output layer[20]. Besides in this model, weight values which are randomly given at first are continuously altered by comparing predicted outputs in training process with actual output values and errors are back propagated until connection weight values which minimize errors are arranged[21]. In this study, Levenberg-Marquardt (LM) learning algorithm which is quite an effective optimization method is applied to balance weights[22]. Fig. 1 presents how each cell in input, hidden and output layers receives NET weighted total output of previous layer as output. NET value is calculated by eqn. 1:

$$NET_{pj} = \sum_{i=1}^{D} A_{ij} C_{pi} + \theta_j \qquad (1)$$

Here D is the size of input vector, θ_j is bias, A_{ij} is the weight group between input and intermediary layers, C_{pi} is output group of input layer for p sample. Every single cell in hidden and output layer produces f (NET) output by passing NET value from a non-linear transfer function. This widely-used transfer function is expressed as:

$$f(NET) = \frac{1}{1 + e^{-NET}} \qquad (2)$$

In training level, for p sample, total error H_p is calculated according to the subtraction of the squares of actual outputs from predicted outputs as in eqn. 3:

$$H_p = \sum_{k=1}^{N} \left(G_{pk} - C_{pk}\right)^2 \qquad (3)$$

Here N is iteration number, for G_{pk} and C_{pk} line and p sample they are actual and predicted output values. Each connection weight is renewed by A_{ij} eqn. 4:

$$A_{ij}^{new} = A_{ij}^{old} - \left[J^T J + \mu I\right]^{-1} J^T H_p \qquad (4)$$

Here J represents Jacobean matrix having weight-dependent derivatives of errors; J^T, Jacobean matrix's transpose; I, unit matrix and μ represents a parameter affecting convergence speed. As μ value increases equation turns into bias reduction algorithm, when decreased it turns into Gauss-Newton algorithm.

EXPERIMENTAL

Study area, Kayseri has 38°56'N-34°24'E coordinates and located in the center of Turkey. The area of this city having 1,165,088 population is 16,917 square kilometers[23]. Air quality monitoring network unit of the Ministry of Environment and Forestry conducts measurement in 4 different regions. But aside from main station, the other measurement locations are far away from the city center. Taking this into account, during 18 months, daily data obtained only from main station in city center were used within the scope of this study[24]. Distribution graphics of PM_{10} concentrations in this process is shown in Fig. 2.

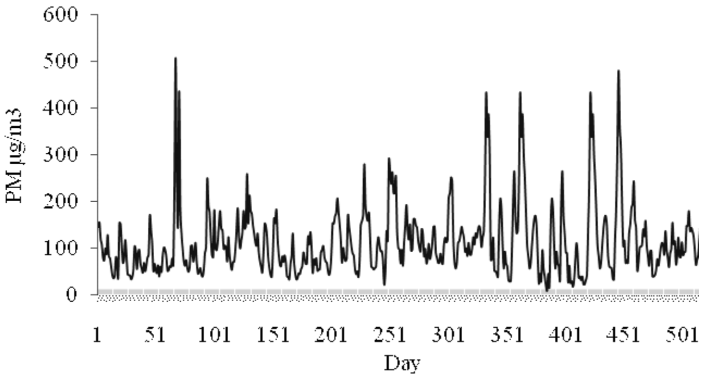


Fig. 2. Daily changes of PM_{10} concentration in 18 month period

Initially correlation between PM_{10} parameter and other input parameters is evaluated by taking statistical analysis of data. Statistical summary of the used air quality parameters is given in Table-1.

TABLE-1
STATISTICAL VALUE OF KAYSERI'S AIR QUALITY PARAMETERS

Parameters	Average	Minimum	Maximum	Standard division	Correlation with PM_{10}
PM_{10} (µg/m^3)	120	11	507	85.89	1.000
SO_2 (µg/m^3)	357	122	1132	124.70	0.511
NO (µg/m^3)	80	14	749	77.08	0.579
NO_2 (µg/m^3)	176	12	871	103.11	0.641
NO_x (µg/m^3)	256	21	765	169.90	0.636
CO (µg/m^3)	466	123	678	175.00	0.471
W Wind speed (m/sn)	1.9	0	12	1590	-0.312
Air temperature (ºC)	17	-23	38	15.76	0.134

In the study, correlation coefficient (R^2) was used as comparison criteria while determining the best ANN structure. Formulations R^2 used in the study are given below:

$$R^2 = \frac{Q_{s0} - Q_s}{Q_s} \tag{5}$$

$$Q_{s0} = \sum_{i=1}^{n} (Q_{si(measured)} - Q_{s(mean)})^2 \tag{6}$$

$$Q_s = \sum_{i=1}^{n} (Q_{si(measured)} - Q_{s(simulated)})^2 \tag{7}$$

where, $Q_{si(measured)}$ and $Q_{si(simulated)}$ are PM_{10} measurement and ANN model estimation values, respectively with the mean PM_{10}, Q_s (mean).

Five input vector SO_2, NO_2, CO, wind speed, air temperature and 524 data set consisting of PM_{10} as output vector; 400 of them to training set and remaining 124 was left for test set to evaluate ANN program's proximity performance to actual values. After that, three different input combinations from input data are formed in order to obtain best results. These are:

i. SO_2 + NO_2 + Air temperature
ii. SO_2 + NO_2 + NO_X + Wind speed
iii. SO_2 + NO_2 + CO + NO_X + Wind speed+ Air temperature

These formed input combinations were trained by Levenberg-Marquet (LM) learning algorithm and as transfer function sigmoid and tangent hyperbolic transfer functions were tried. Various iteration number and intermediary layer cell numbers were obtained after many trials and errors. Table-2 shows application methodology of model variables.

TABLE-2
APPLICATION METHODOLOGY OF ANN MODEL VARIABLES

ANN structure	Iteration step number	Hidden layer number	Neuron number in hidden layer
i	100-250-1000	1-2-3	2-3-4-5
ii	100-250-1000	1-2-3	2-3-4-5
iii	100-250-1000	1-2-3	2-3-4-5

Within the scope of this study, each data set distribution, model structure and iteration step are evaluated within themselves. Such as, Combination iii; initially in single hidden layer by using 2, 3, 4 and 5 neurons, in the same structure respectively in 100, 250 and 1000 iteration step, training and consequent test levels are performed. In the same data set distribution, by increasing hidden layer number, neuron numbers and iteration steps indicated in Table-2 are applied, respectively. It is observed that in all these formed models, performance values of training level for R^2 is between 0.508-0.903.

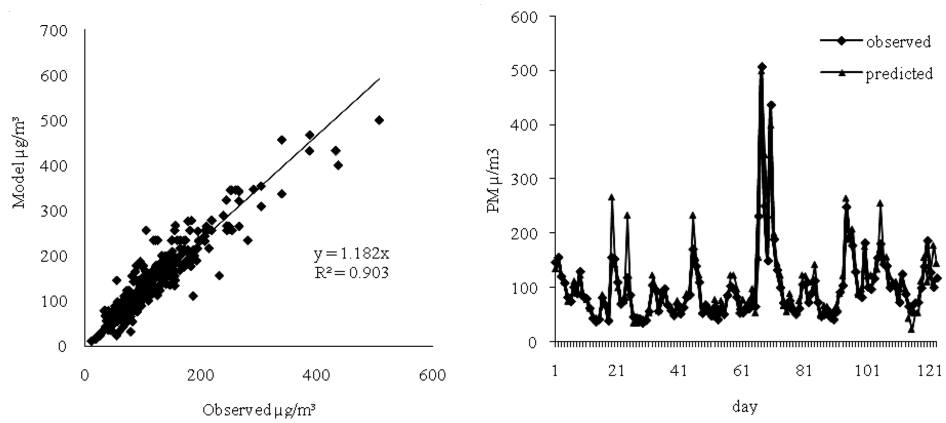
RESULTS AND DISCUSSION

Three different training data set determined, it was observed that after 250 iteration steps, error value remained constant irrespective of model structure. Thus it was concluded that increase in iteration step generally did not affect training performance and the change in R^2 values in this level stemmed from variations in model structure. Amongst all these combinations formed *via* these model trials, Multi-Layer ANN structures which gave the best results are shown in Table-3.

TABLE-3
ANN STRUCTURES WHICH GAVE THE BEST RESULT

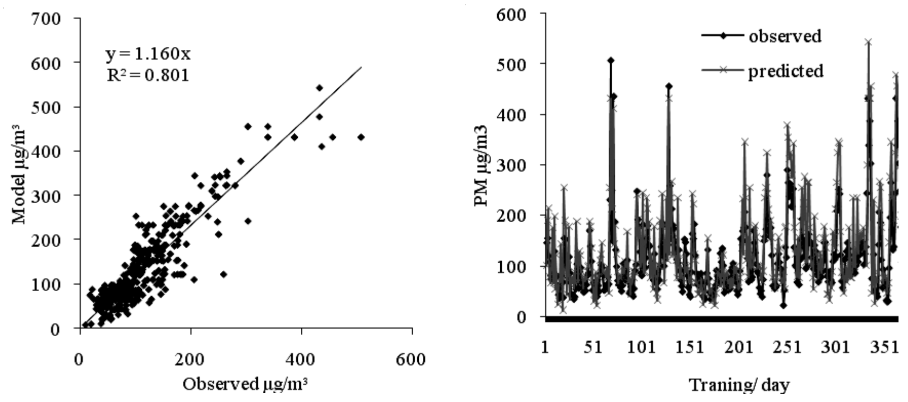
Combinations	ANN structures	Determination coefficient (R^2)
i	[2 4 1]	0.508
ii	[3 3 1]	0.764
iii	[5 5 1]	0.903

It was observed that input consisting of SO_2, NO_2, CO, NO_X, wind speed, air temperature and values formed as combination 3 and ANN structure where PM is output values of $R^2 = 0.903$ and predictions gave more accurate results compared to other trials. The best model performance values are obtained in model step where there are two hidden layers and 5 neurons in hidden layers, in 250 training iteration numbers and in conditions where sigmoid is used as transfer function. In Fig. 3a and 3b graphics of Multi-layer ANN structure, the one that gave the best result, are shown. Moreover Multi-layer ANN prediction of this last combination is compared with MRA. In Fig. 4a, for combination (iii), estimations obtained from MRA with observed PM_{10} are indicated. In Fig. 4b, for MRA model estimated and measured PM_{10} values' time-dependent change graphics are illustrated.



(a) (b)

Fig. 3. Comparison of PM_{10} estimations with observed PM_{10} in Multi-layer ANN structure that gave the best result (a), time-dependent change of Multi-layer ANN structure's PM_{10} output values' estimated and measured values in test phase (b)



(a) (b)

Fig. 4. For combination (iii), comparison of PM_{10} estimations obtained from MRA with observed PM_{10} (a), For MRA model estimated and measured PM_{10} values' time-dependent change graphics (b)

Conclusion

In this study, by using multi-layer artificial neural network model, PM_{10} concentration prediction was made *via* air quality data measured daily in Kayseri during 18 months. Input parameters were used as 3 separate combinations and effectiveness levels of each combination were determined. Accordingly the most effective result was obtained from the last combination where input was SO_2, NO_2, CO, NO_X, wind speed, air temperature and PM_{10} was output. Besides ANN estimations were compared with MRA estimations for combination iii. These comparisons revealed that ANN performance was better than MRA performance. As a conclusion it is suggested that since ANN model offers more accurate and reliable PM_{10} predictions, it can be used as a very effective model in air quality management.

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