Asian Journal of Water, Environment and Pollution, Vol. 15, No. 1 (2018), pp. 57–65.
DOI 10.3233/AJW-180006

Comparison of Different Artificial Neural Networks Techniques and Autoregressive Models for Forecasting of PM_{10}

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Received November 6, 2017; revised and accepted December 8, 2017

Abstract: Atmospheric particulate matter (PM_{10}) is one of the pollutant affecting human health significantly and has become a global issue. Data collected during three years in an urban area of Allahabad, Uttar Pradesh, India, are analysed and compared for 1-month ahead forecasting of PM_{10} using four models: Levenberg algorithm (LM) based artificial neural network (ANN), radial basis function neural network (RBFNN), generalized regression neural network (GRNN) and autoregressive (AR) model. Measured PM_{10} concentration are used as input to forecast the monthly averaged concentration of PM_{10} for one month ahead. The mean absolute percentage error (MAPE) for AR models varies from 10.20% to 32.78% whereas MAPE for ANN, RBFNN and GRNN are found 4.75%, 13.40% and 11.43% respectively, showing ANN model with LM algorithm forecast PM_{10} at one month ahead better than RBFNN, GRNN and AR models. In addition GRNN forecast is better than RBFNN with good accuracy. The average values of PM_{10} for Bharat Yantra Nigam Allahabad and Ardali Bazar Varanasi are found to be 182.16 and 262 respectively, showing Varanasi has high value of PM_{10}. This study is useful for researcher working in forecasting of PM_{10}.

Key words: Artificial neural network, forecasting, PM_{10}, radial basis function neural network, generalized regression neural network and autoregressive model.

Introduction

During past years several effects of PM_{10} on monuments soiling, building, environment and human health have become an active research area. PM_{10} is particulate matter which has effective aerodynamic diameter smaller than 10 µm is one of the most dangerous pollutants. PM_{10} penetrates respiratory systems affecting inhalation and cause respiratory problem (Turner et al., 2011). High PM_{10} levels have been correlated to increase in hospital admissions for lung and heart diseases (Ostro et al., 1999). Several studies (Dockery and Pope, 1994; Katsouyanni et al., 1997) present even small concentration of PM_{10} in ambient air affecting human healths. $PM_{2.5}$ (aerodynamic diameter below 2.5 mm) impacts more negatively the human health than PM_{10}, since it penetrates more deeply in the respiratory system. Due to these issues, accelerated interest in formation and control of PM_{10} and $PM_{2.5}$ has increased now a days.

Meteorological conditions influence accumulation of PM_{10} in atmosphere (Amodio et al., 2012; Rodriguez et al., 2001). The PM_{10} elevated conditions are results of unfavourable meteorological conditions (Grivas and

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Chaloulakou, 2006; Carnevale et al., 2010). Therefore it is necessary to improve the air quality in major population rich cities. It is also important to develop such new techniques for formulation of improvement strategies. In order to design the health warning guidelines, forecasting of an accurate pollutant by means of location and time is necessary. Many authors [(Hooyberghs et al. (2005), Auder et al. (2016**)**, Sonaje et al. (2013), Bincofiore et al. (2017), Kukkonen et al. (2003), Perez and Reyes (2006), Ghazi et al. (2009), Barbes et al. (2009), Ozel and Cakmakyapan (2015), Alkasassbeh et al. (2013), Skyrzypski and Szakiel (2008), Baawain et al. (2014), Elminir and Galil (2006), Yadav and Nath (2017)) used different methods of PM_{10} forecasting based on Artificial Neural Networks and Autoregressive methods.

In India there is huge number of people living with higher level of pollution with quite serious issue. Delhi is possibly one of the mega polluted city in India where concentration of air pollutant increased more than safe limit in the month of November 2017. Kanpur is second most polluted city. Air pollution in busy market areas of Allahabad is quite a serious issue. In this study artificial neural network (ANN), radial basis function neural network, generalized regression neural network and autoregressive models are developed and compared to forecast one month ahead PM_{10} value for Allahabad city.

Methods

Data Compilation

The selected area for present study is Allahabad district of Uttar Pradesh. Allahabad district is situated at 25° 28′ N latitudes 81° 50′ E. at the meeting point of the three sacred rivers of Ganges, Yamuna and Saraswati and located in south eastern part of Uttar Pradesh. This is one of the major and largest districts of Uttar Pradesh state of India. According to the 2011 census Allahabad district has a population of 5,959,798, roughly equal to the nation of Eritreaor the US state of Missouri. This gives it a ranking of 13th in India (out of a total of 640).

Monthly time series data of PM_{10} during 2013-2015 for Bharat Yantra Nigam, Allahabad was taken from Uttar Pradesh Pollution Control Board (UPCB) Lucknow. The values of PM_{10} are shown in Table 1.

Table 1: Measured PM_{10}

Month	*PM_{10} for year 2013*	*PM_{10} for year 2014*	*PM_{10} for year 2015*
Jan	247	274	216.4
Feb	252	314	236
March	205	246	203
Apr	198	198	234
May	176	240	233
June	217	209	254
July	186	246	239
Aug	206	242	235
Sep	218	214	228
Oct	269	219	233
Nov	236	231	230
Dec	256	206	260
Average	22.2	236	233.5
Max	269	314	260
Min	176	198	203

Artificial Neural Network

The ANN model is developed using artificial neural network fitting tool (nftool) for PM_{10} forecasting. The nftool utilizes standard two layers feed forward neural network, Levenberg-Marquardt (LM) training algorithm and is appropriate for static fitting problems. The training is performed with scaled conjugate gradient (Yadav et al., 2014). The input and target data are mapped into –1 to 1 and data is randomly divided into 60% training, 20% testing and 20% validation. The training data is used for training ANN models, testing data for measuring performance of network and validation data for generalization capacity of network. The error in networks is measured by performance plot which is a curve between mean square error (MSE) and number of epochs (one complete sweep of training, testing and validation). The performance plot shows MSE in training, testing and validation data. The MSE plot has upper curve in validation data set and lower curve in training data set. The training stops automatically as validation error stops decreasing which is specified by increase in validation data MSE and network with minimum MSE in validation data set is called trained network. Training multiple times will produce unique results due to random initialization of connection weights and different initial conditions.

The hidden layer neurons is calculated by equation (Chow et al., 2012), where h_n and s_n are number of hidden layer neurons and data samples in ANN model, i_n and o_n denote number of input and output parameters.

$$h_n = \frac{i_n + o_n}{2} + \sqrt{s_n} \quad (1)$$

The sensitivity test is performed to validate the number of hidden layer neurons by calculating change in prediction error (MAPE) when number of hidden layer neurons is changed ±5 from hidden layer neurons calculated by equation (1). The mean absolute percentage error (MAPE) is given by equation (2) and ANN architecture with least MAPE is used for PM_{10} forecasting.

$$\text{MAPE} = \left(\frac{1}{n} \sum_{i=1}^{n} \left| \frac{AP_{i(AR)} - AP_{i(actual)}}{AP_{i(actual)}} \right| \right) \times 100 \quad (2)$$

where $AP_{i(AR)}$ forecasted value of PM_{10}, $AP_{i(actual)}$ is actual value of PM_{10} and n is number of air pollutant data samples.

Radial Basis Function Neural Network (RBFNN)

The RBFNN is an alternative to multilayer perceptron neural network and acts as universal approximator. The RBFNN uses activation function as radial basis function (Figure 1). The output is a linear combination of neurons and radial basis functions. It has simple structure and faster training procedure. It executes accurate interpolation on a group of data features in a multidimensional space and can be used for function approximation, classification and prediction. It consists of three layers: an input layer, a hidden layer with radial basis function and linear output layer. The input is modelled in terms of real number vector. The output is scalar function of input vector which is given by following equations.

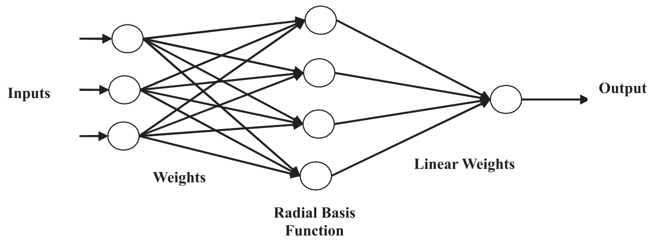

Figure 1: RBFNN architecture.

$$y(x) = \sum_{i=1}^{N} w_i f\left(\left\| x - c_i \right\|\right) \quad (3)$$

$$f\left(\left\| x - c_i \right\|\right) = \exp\left[-\beta \left\| x - c_i \right\|^2\right] \quad (4)$$

$$\lim f\left(\left\| x - c_i \right\|\right)_{\|x\| \to \infty} = 0 \quad (5)$$

where N are hidden layer neurons, c_i is centre vector for neuron i and w_i is the weight of neuron i in linear output neuron. The norm is Euclidean distance and Gaussian function is used for radial basis function. The parameters c_i, w_i and β are calculated by optimization techniques that fit between $y(x)$ and data.

Generalized Neural Network (GRNN)

GRNN is a class of radial basis network exploited for function approximation. The GRNN syntax is net = newgrnn (P, T, spread) where P is a matrix of input vectors; T is a matrix of target vectors. The smaller spread is applied to fit the data compactly than the normal distance between input vectors but larger spread is worked to fit the data smoothly. The newgrnn generates a two-layer network. The first layer has newrbe network which initiates as many neurons as there are input/target vectors, which computes weighted inputs with dist and net input with netprod. It has biases all set to 0.8326/spread consequential in radial basis functions. The second layer holds purelin neurons, evaluates weighted input with normprod, and net inputs with netsum.

Autoregressive Model

In statistics application an autoregressive (AR) model is a random process representation to describe time varying process. The AR model discusses about linear dependency of output on its own previous values on a stochastic term (an imperfectly predictable term); thus the model is in the form of a stochastic difference equation. When AR model is combined with moving-average (MA) model it is called autoregressive moving-average (ARMA). An autoregressive model of order p is denoted by $AR(p)$. It is defined as

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \varepsilon_t \qquad (6)$$

where $\varphi_i \ldots \varphi_p$ are the parameters of the model, c is a constant and ε_t is a white noise. This can be written by using the backshift operator B.

$$X_t = c + \sum_{i=1}^{p} \phi_i B_i X_t + \varepsilon_t \qquad (7)$$

so that, moving the summation term to the left side and using polynomial notation, we have

$$\phi(B) X_t = c + \varepsilon_t \qquad (8)$$

The AR models can be implemented by Burge method (BM) and Yule Walker method (YWM). The syntax in matlab codes are as follows:

[ar_coeffs noise variance] = arburg(y, order) for BM

[ar_coeffs noise variance] = aryule (y, order) for YWM

where y is data samples.

Results and Discussions

The forecasting accuracy of ANN, RBFNN, GRNN and AR models using relevant input variables given by Rapid Miner is calculated with MAPE as suggested by Lewis (1982). The MAPE $\leq$ 10% shows high prediction accuracy, 10% $\leq$ MAPE $\leq$ 20% shows good prediction, 20% $\leq$ MAPE $\leq$ 50% specified reasonable prediction. MAPE $\geq$ 50% indicates inaccurate forecasting. The MAPE for ANN model is shown in Table 2. The least MAPE is 4.75% showing highly accurate forecasting. The performance plot, error histogram plot, error plot and gradient plot are shown in Figure 2, Figure 3, Figure 4 and Figure 5 respectively. The comparison between measured and forecasted PM_{10} by ANN is shown in Figure 6.

Table 2: Forecasting accuracy calculation

Hidden layer neurons	*MAPE (%)*
4	4.75
5	6.06
6	7.88
7	7.00
8	6.02
9	7.19
10	5.95
11	6.13
12	7.51
13	8.95
14	9.31

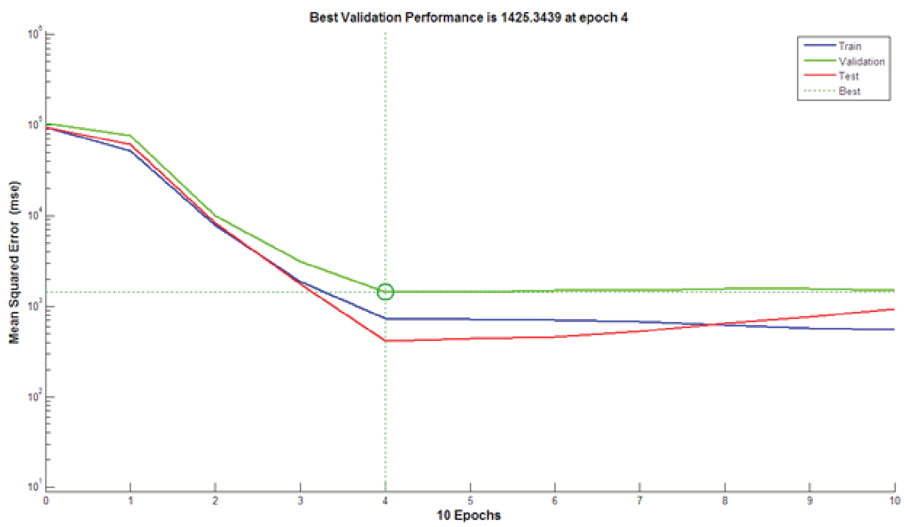

Figure 2: Performance plot.

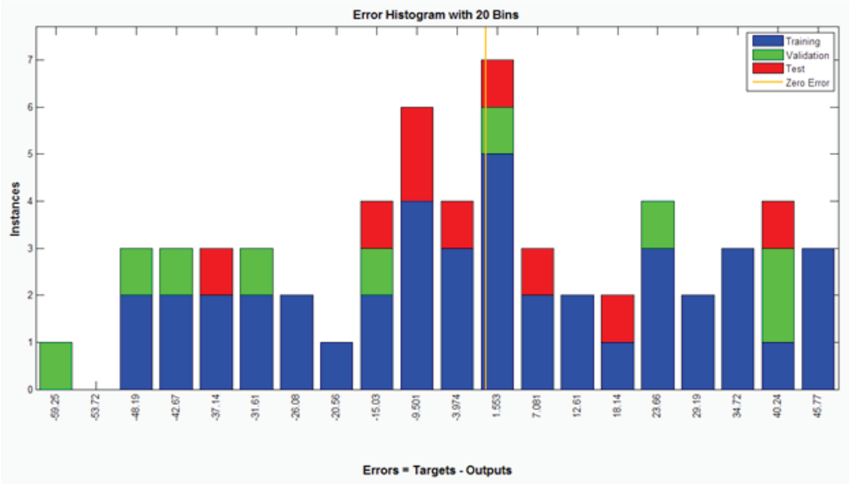

Figure 3: Error histogram plot.

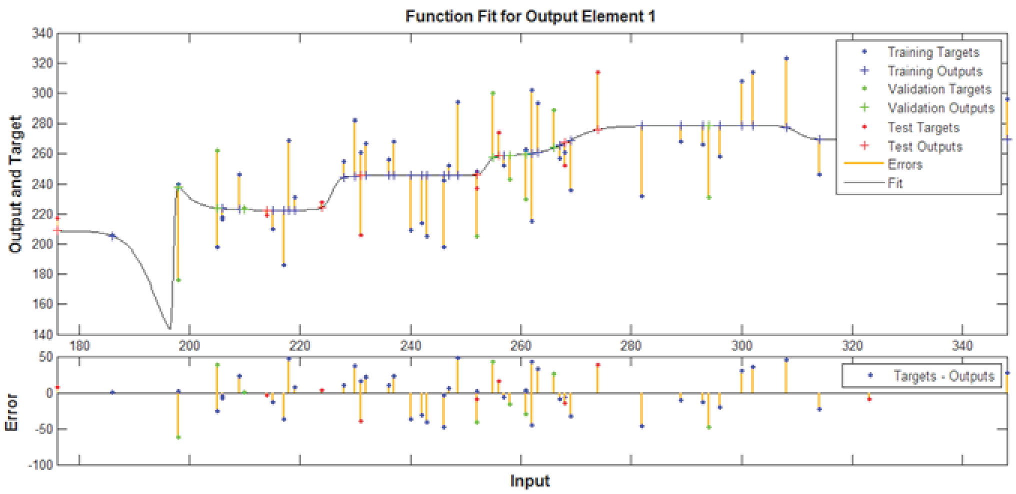

Figure 4: Error plot.

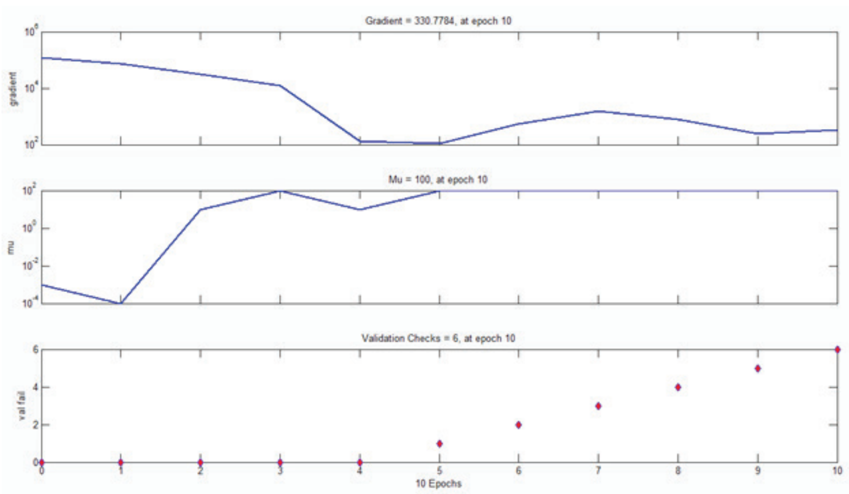

Figure 5: Gradient plot.

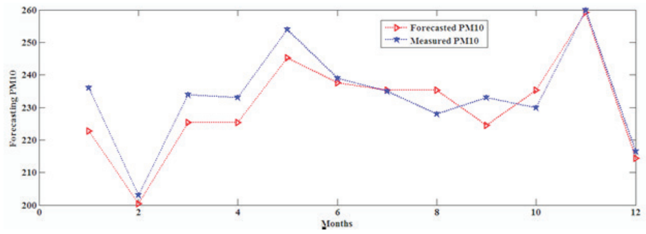

Figure 6: Comparison between measured and forecasted PM_{10} by ANN.

The MAPE in RBFNN and GRNN models are 13.40% and 11.43% respectively. The comparison between measured and forecasted PM_{10} by RBFNN and GRNN are shown in Figures 7 and 8.

The AR(1) and AR(5) models are developed in Matlab (R2011a) using PM_{10} values shown in Table 1. The data of Figure 3 are used for validation of AR models. The AR models incorporate Burge and Yule Walker method. The forecasting value of 1-month ahead PM_{10} value using Burge and Yule Walker method in AR models are shown in Figures 9 to 12. The MAPE, RMSE and MBE used to test forecasting accuracy of AR models are shown in Tables 3 and 4.

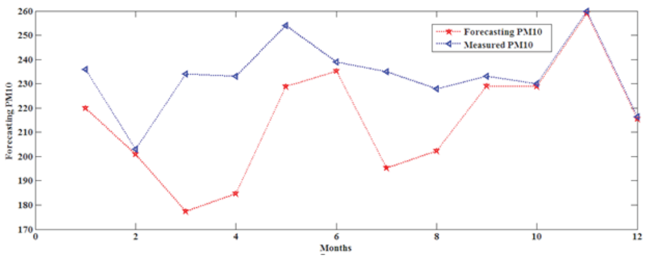

Figure 7: Comparison between measured and forecasted PM_{10} by RBFNN.

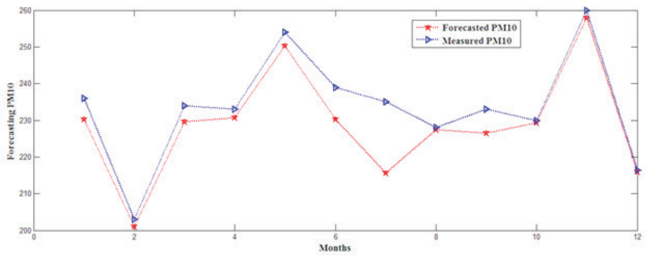

Figure 8: Comparison between measured and forecasted PM_{10} by GRNN.

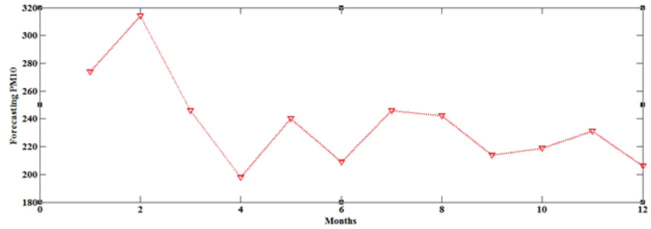

Figure 9: Forecasting of PM_{10} using Burge method in AR(1) model.

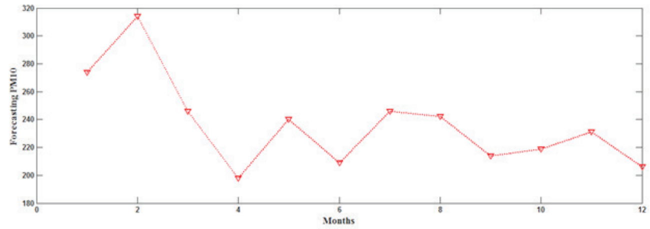

Figure 10: Forecasting of PM_{10} using Burge method in AR(5) model.

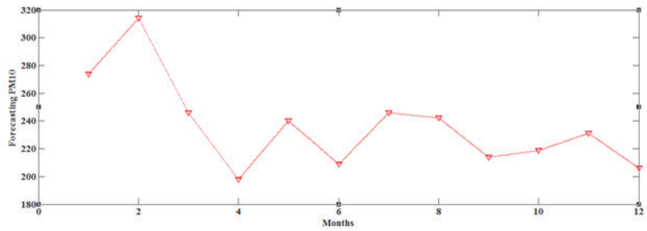

Figure 11: Forecasting of PM_{10} using Yule Walker method in AR(1) model.

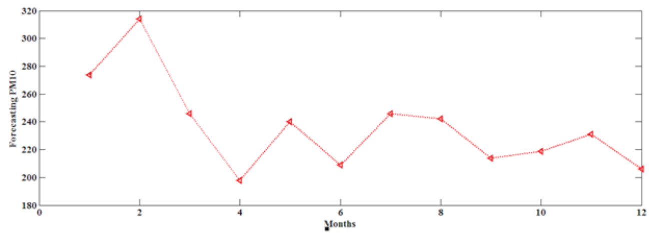

Figure 12: Forecasting of PM_{10} using Yule Walker method in AR(5) model.

Table 3: Burge method based AR models

Model	*MAPE (%)*	*RMSE*	*MBE*	*Highlights*
AR (1)	14.23	37.76	-34.09	Good forecasting
AR(5)	10.20	26.85	-22.41	Good forecasting

Table 4: Yule Walker method based AR models

Model	*MAPE(%)*	*RMSE*	*MBE*	*Highlights*
AR (1)	32.78	84.75	-77.89	Reasonable forecasting
AR(5)	31.13	80.29	-73.98	Reasonable forecasting

It is found that ANN model developed with nftool has least MAPE of 4.75% showing good forecasting of PM_{10}.

Case Study: Varanasi City

The comparison of PM_{10} for cities of Allahabad and Varanasi for 2016 are shown in Table 5. The average value of PM_{10} in Bharat Yantra NigamAllahabad and Ardali Bazar Varanasi are found to be 182.16 and 262 respectively.

The multiple linear regression model is used to develop correlations of PM_{10} in terms of atmospheric pressure, solar radiation and wind speed (Table 6). The normalized value is used to develop MLR models. It is

Table 5: Comparison of PM_{10}

Months	*Varanasi PM_{10}($\mu g/m^3$)*	*Allahabad PM_{10} ($\mu g/m^3$)*
Jan	452.16	238
Feb	328.28	253
March	308.24	227
Apr	330.55	233
May	231.32	242
June	141.06	246
July	81.62	93
Aug	93.11	39
Sep	109.01	59
Oct	346.10	159
Nov	378.53	207
Dec	345.77	190
Average	262.17	182.16
Max	452.16	253
Min	81.62	39

Table 6: MLR Models

Models	*Correlations*	*MAPE (%)*	*RMSE*
MLR-1	$PM_{10} = (0.4724 - 0.2462SR - 0.1325WS - 0.0888AP) \times 979.310 + 12.060$	51.18	0.1164
MLR-2	$PM_{10} = (0.3865 - 0.1671SR - 0.1109WS) \times 979.310 + 12.060$	39.97	0.1118
MLR-3	$PM_{10} = (0.3555 - 0.2075SR - 0.0785AP) \times 979.310 + 12.060$	52.86	0.1191
MLR-4	$PM_{10} = (0.3813 - 0.0987WS - 0.0559AP) \times 979.310 + 12.060$	51.41	0.1183
MLR-5	$PM_{10} = (0.2952 - 0.1418SR) \times 979.310 + 12.060$	42.31	0.1136
MLR-6	$PM_{10} = (0.3408 - 0.0910WS) \times 979.310 + 12.060$	42.47	0.1134
MLR-7	$PM_{10} = (0.3017 - 0.0520AP) \times 979.310 + 12.060$	51.96	0.1198

found that as atmospheric pressure, solar radiation and wind speed increases concentration of PM_{10} decreases.

To develop correlation of PM_{10} in terms of wind speed, monthly average value of wind speed are utilized and correlation as shown below:

$$PM_{10} = -100.59\mathrm{WS} + 8.44.6021 \qquad (9)$$

Conclusions

Neural network fitting tool (nftool), Radial Basis Function Neural Network (RBFNN), Generalized Neural Network (GRNN) and Auto Regressive (AR) models are developed and compared for forecasting of PM_{10} at one month ahead for Allahabad city in India. The key originality of this work is that developed model can be used for forecast PM_{10} for Allahabad city. Moreover the developed correlations of PM_{10} in terms of meteorological variables can be used to estimate PM_{10} for Allahabad and Varanasi cities. The mean absolute percentage error for nftool, RBFNN and GRNN are 4.75%, 13.40% and 11.43%, showing nftool forecast PM_{10} one month ahead better than RBFNN and GRNN. For further validation nftool, RBFNN and GRNN are compared with AR model developed with Burge and Yule Walker method. The MAPE for Burge Method Based AR(5) model is 10.20% and MAPE for Yule Walker Method Based AR(5) model is 31.13% showing good forecasting of Burge Method Based AR(5) model over Yule Walker Method Based AR(5) model. The Burge Method Based AR(5) model forecast better than RBFNN and GRNN.

Future research work is focussed on evaluation of forecasting accuracy of air pollutants at different time scale using different ANN models for different sites.

Acknowledgement

The authors acknowledge the Uttar Pradesh Pollution Control Board (UPPCB) Lucknow, and Central Pollution Control Board (CPCB) New Delhi, India for providing online air pollutant data for this research.

References

Alkasassbeh, M., Mouhammad, Sheta, F.A., Faris, H. and H. Turabieh (2013). Prediction of PM10 and TSP Air Pollution Parameters Using Artificial Neural Network Autoregressive, External Input Models—A Case Study in Salt, Jordan. *Journal of Scientific Research*, **14(7):** 999-1007.

Amodio, M., Andriani, E., de Gennaro, G., DemarinisLoiotile, A., Di Gilio, A. and M.C. Piacentino (2012). An integrated approach to identify the origin of PM10 exceedances. *Environ. Sci. Pollut. Res.*, **19:** 3132-3141.

Baawain, S.M. and A.S.A. Serihi (2014). Systematic Approach for the Prediction of Ground-Level Air Pollution (around an Industrial Port) Using an Artificial Neural Network. *Aerosol and Air Quality Research*, **14:** 124-134.

Barbes, L., Neagu, C., Melnic, C., Ilie, C. and M. Velicu M (2009). The Use of Artificial Neural Network (ANN) for Prediction of Some Airborne Pollutants Concentration in Urban Areas. *Rev. Chim. (Bucureti)*, **60(3)**.

Biancofiore, F., Busilaccio, M., Verdecchia, M., Tomasseti, B., Aruffo, E., Bianco, S., Tommaso, D.S., Colangeli, C., Rosatelli, G. and D.P. Carlo (2017). Recursive neural network model for analysis and forecast of PM_{10} and $PM_{2.5}$. *Atmospheric Pollution Research*, **1(8):** 1042-1309.

Carnevale, C., Pisoni, E. and M. Volta, M. (2010). A non-linear analysis to detect the origin of PM10 concentrations in Northern Italy. *Sci. Total. Environ.*, **409:** 182-191.

Chow, S.K.H., Lee, E.W.M. and D.H.W. Li (2012). Short-term prediction of photovoltaic energy generation by intelligent approach. *Energy and Buildings*, **55:** 660-667.

Elminir, K.H. and A.H. Galil (2006). Estimation of air pollutant concentration from meteorological parameters using Artificial Neural Network. *Journal of Electrical Eng*, **57(2):** 105-110.

Frederick, M. (1996). Neuroshell 2 Manual. Ward Systems Group Inc.

Ghazi, S. and T.M. Khadir (2009). Recurrent Neural Network for multi-steps ahead prediction of PM_{10} concentration. *J. Automation and System Engineering*.

Grivas, G. and A. Chaloulakou (2006). Artificial neural network models for prediction of PM10 hourly concentrations, in the Greater Area of Athens, Greece. *Atmos. Environ.*, **40:** 1216-1229.

http://www.cpcb.gov.in/CAAQM/frmUserAvgReportCriteria.aspx.

http://www.uppcb.com/air_quality_nov.html.

Hooybergs, J., Mensink, C., Dumont, G., Fierens, F. and O. Brasseur (2005). A neural network forecast for daily average PM_{10} concentrations in Belgium. *Atmospheric Environment*, **39:** 3279-3289.

Kukkonen, J., Partanena, L., Karppinena, A., Ruuskanenb, J., Junninenb, H., Kolehmainenb, M., Niskab, H., Dorling, S., Chattertonc, T., Foxalld, R. and G. Cawleyd (2003). Extensive evaluation of neural network models for the prediction of NO2 and PM10 concentrations, compared with a deterministic modelling system and measurements in central Helsinki. *Atmospheric Environment*, **37:** 4539-4550.

Lewis, C.D. (1982). International and Business Forecasting Methods. London: Butterworths.

Ostro, B., Chestnut, L., Vichit-Vadakan, N. and A. Laixuthai (1999). The impact of particulate matter on daily mortality in Bangkok, Thailand. *J. Air Waste Manag. Assoc.*, **49:** 100-107.

Ozel, G. and S. Chakmakyapan (2015). A new approach to the prediction of PM10 concentrations in Central Anatolia Region, Turkey. *Atmospheric Pollution Research*, **6:** 735-741.

Perez, P. and J. Reyes (2006). An integrated neural network model for PM10 forecasting. *Atmospheric Environment*, **40:** 2845-2851.

Rodriguez, S., Querol, X., Alastuey, A., Kallos, G. and O. Kakaliagou (2001). Saharan dust contribution to PM10 and TSP levels in Southern and Eastern Spain. *Atmos. Environ.*, **35:** 2433-2447.

Skyrzypski, J. and J.E. Szakiel (2008). Neural Network Prediction Models as a Tool for Air Quality Management in Cities. *Journal of Environment Protection Engineering*, **34:** 130-137.

Sonaje, N.P., Mane, S.J. and A.S. Kote (2013). Modelling of Respirable Suspended Particulate Matter Concentration Using Artificial Neural Networks in an Urban Area. *International Journal of Engineering Science and Technology*, **3(4):** ISSN. 2250-3498.

Turner, M.C., Krewski, D., Pope, C.A., Chen, Y., Gapstur, S.M. and M.J. Thun (2011). Longterm ambient fine particulate matter air pollution and lung cancer in a large cohort of never-smokers. *Am. J. Respir. Crit. Care Med.*, **184:** 1374-1381.

www.inf.ufrgs.br/~engel/Common/CMP121/RBF_MATLAB.pdf.

Yadav, A.K., Malik, H. and S.S. Chandel (2014). Selection of most relevant input parameters using WEKA for artificial neural network based solar radiation prediction models. *Renewable and Sustainable Energy Reviews*, **31:** 509-519.

Yadav, V. and Satyendra Nath (2017). Forecasting of PM10 Using Autoregressive Models and Exponential Smoothing Technique. *Asian Journal of Water, Environment and Pollution*, **14:** 109-113.