"COMPARISON OF DIFFERENT ARTIFICIAL NEURAL NETWORK MODELS FOR PREDICTING RESPIRABLE PARTICULATE MATTER (PM_{10}) CONCENTRATION IN BENGALURU CITY"

Chethan D M [1], Dr B Santhaveerana Goud [2]

[1] PG Student, Department of Civil Engineering, UVCE, Bengaluru University, Bengaluru, Karnataka.560056 Email: [2] Professor, Department of Civil Engineering, UVCE, Bengaluru University, Bengaluru, Karnataka.560056

Abstract - *Rapid increase in industrialization and urbanization is a threat to the public health because of adverse impact on the quality of air caused by the accumulation of unwanted particles. Studies conducted in Delhi have also documented the levels of different pollutants in the air have reached an alarming heights. From past few decades Bengaluru is also growing in an exponential way caused concern about the quality of air, it happens to be sixth most polluted city in India. Hence the present study focused on predicting PM_{10} concentrations at four different air quality monitoring stations of Bengaluru by the application of Artificial neural network models(ANN). An attempt also is being made to assess the efficiency of models in the predictions. Six years daily average PM_{10} data was used for the study, Four different ANN models namely Feed forward back propagation neural network(FFBP), ELMAN neural network, Recurrent neural network(RNN) and Nonlinear Autoregressive with Exogenous input(NARX) were used in predictions. The assessment of efficiency was based on the correlation coefficient(R) and Mean Squared Error (MSE). The results have shown that NARX model was found to be better than other models with a correlation coefficient of 0.88774 and Mean Squared Error of 0.008094. Hence for the city of Bengaluru NARX model may found to be more suitable for prediction of PM_{10} concentrations.*

Key Words: Particulate matter; Artificial neural network; feedfarward back propagation; Recurrent neural network; Nonlinear Autoregressive exogenous input.

1.INTRODUCTION

In the midst of rapid increase in industrialization and urbanization, cities in developing countries are witnessing unprecedented population growth. Urban expansion, coupled with the surge in industrial activities, increased automobiles poses a grave threat to the natural environment, including vital resources such as air, water, and soil. The Continuous addition of harmful substances into the atmosphere, collectively known as atmosphere pollution, emerges as a pressing concern with far-reaching implications for human health, property, and ecological balance https://www.afro.who.int/health-topics/air-pollution. Among the myriad forms of environmental pollution, air pollution stands out as a critical global challenge, The term encompasses any physical, chemical, or biological agent that disrupts the natural composition of the atmosphere, thereby deteriorating its quality and posing health risks to inhabitants. Nowhere this issue is more pronounced than in metropolitan hubs like Bengaluru, where the Air Quality Index (AQI) fluctuates dramatically with each passing season, reflecting the alarming levels of air pollution prevalent in the region (Gurjar et al.2016). Bengaluru ranks 6th among the most polluted cities in India, with the Air quality Index 101 are found to be at alarming levels at some severely polluted areas.

These places are dispersed throughout the city, represent focal points of heightened air pollution, where concentrations of harmful pollutants exceed permissible limits. The immediate impact of such pollutants on respiratory systems underscores the urgency of developing accurate prediction models to serve as early warning systems, safeguarding public health and well-being. While many prediction models attempt to correlate air pollutant concentrations with meteorological conditions. The complexity of these interactions necessitates advanced methodologies.

Traditional deterministic models often fall short in predicting extreme pollutant concentrations and require extensive computational resources, thereby limiting their practical utility (Marjovi et.al 2016; Wang 2017). In contrast, statistical approaches, such as Multiple Linear Regression (MLR) and Auto Regressive Moving Average (ARMA) methods, struggle to capture non-linear patterns and may prove inadequate for extreme concentration scenarios (Li, X Peng et al. 2016). Recognizing these limitations, researchers have increasingly turned to artificial neural network (ANN) models, appreciating their efficiency and predictive accuracy. Artificial neural networks offer a versatile framework capable of effectively managing non linearities, data distortions, and missing values inherent in environmental datasets (Chaloulakou et al. 2003). Comparative studies between ANN models and conventional techniques consistently demonstrate the superior predictive capabilities of neural networks across various domains (Jiang 2004; Ghazi et al 2009. Gundogdu 2009).

This paper focusing on the prediction of PM_{10} concentrations an indicator of air quality at different monitoring stations within Bengaluru, India. Using four ANN models namely NARX, RNN, FFBP, and ELMAN, my study endeavors to identify the most effective predictive model to predict PM_{10} concentration in Bengaluru city. By harnessing the power of neural networks, we aim to assess robust prediction models capable of accurately predicting PM_{10} concentrations, thereby aiding policymakers and stakeholders in formulating proactive measures to combat air pollution and safeguard public health.

2.0 THE STUDY AREA

Bangalore City Located on the Deccan Plateau in southern peninsular India, Bengaluru (formerly Bangalore), the capital of Karnataka state, is the second-fastest-growing metropolitan city in the country. According to the Census of India (2011), Bengaluru's population is about 96,45,551 and it is located at latitude of 12^0 58'18''N and longitude of 77^0 35' 37''E. It is the nation's leading information technology exporter and is popularly known as the "Silicon Valley of India" and also the "Garment capital of India". Bengaluru is situated at an altitude of ~920 m above mean sea level. The climate of the region is classified as seasonal dry tropical savanna climate, with three distinct seasons: summer (March to May), monsoon (June to September), and winter (October to February), City's annual average rainfall is 970mm. and annual average temperature varies from 22^0c to 34^0c.

Four air quality monitoring stations established by Central Pollution Control Board at different locations in Bengaluru namely Bapuji Nagar, Hebbal, Jayanagara, and Hombegowdanagara. The details are as shown in Table 1 and Figure 1

Table 1 Description of Selected locations

Name of the place	Latitude	longitude	Type of place
Bapuji nagar	12°57'24''N	77°32'22''E	Residential
Hebbal	13°02'80''N	77°35'49''E	Industrial and Commercial
Jayanagar (5th block)	12°55'1'' N	77°35'10''E	Residential and Commercial
Hombegowda nagar	12°56'15'N	77°35'47''E	Residential

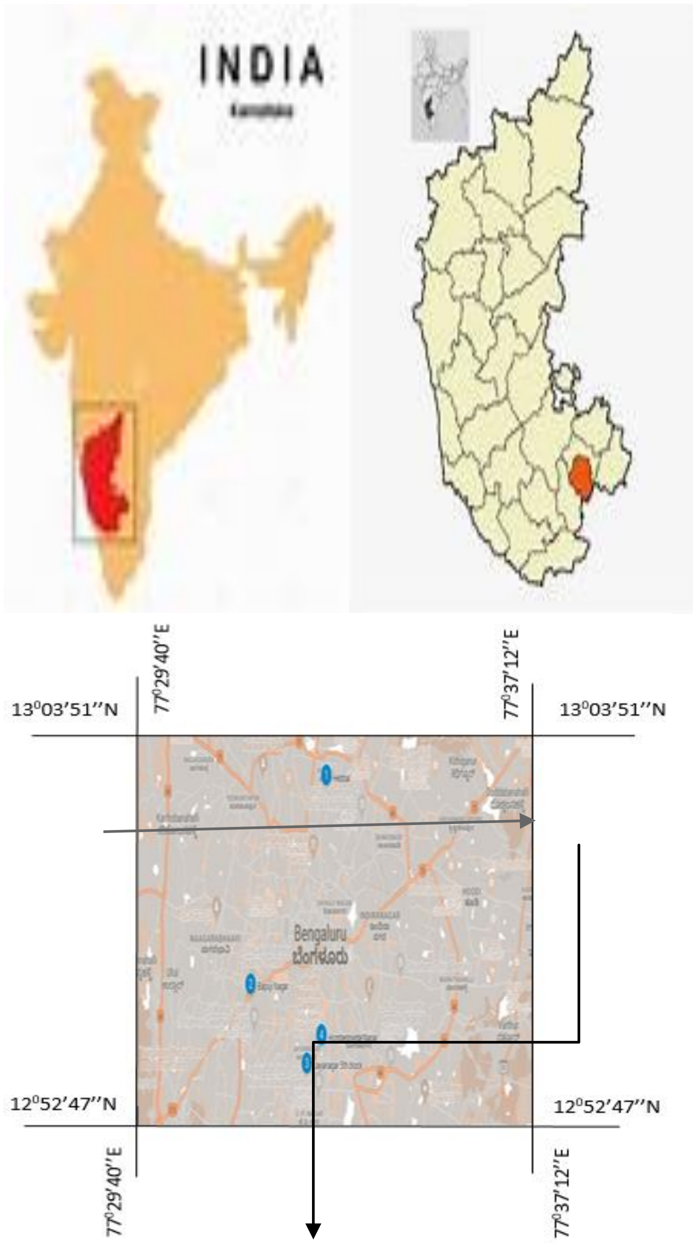

Fig. 1. Locations of Air quality monitoring Stations

3.0 METHODOLOGY FOLLOWED

3.1 Artificial neural networks

For each station, four neural network models were used all of them have different architecture. A series of training algorithms were considered, including error back propagation, conjugate gradient descent and levenberg-Marquardt algorithms. The Levenberg-Marquardt algorithm proved to be the most efficient in our case. This algorithm was designed to approach second-order training speed without computing hessian matrix. Back Propagation is used to calculate the Jacobian of performance w.r.t. weight and bias variables. Each variable is adjusted according to Levenberg-Marquardt method.

The early stopping technique was implemented during the training of different ANN models. The training process was finalized when the selected Mean Squared Error (MSE) reached a minimum. The number of hidden nodes was varied and the corresponding value of the error function was calculated. The number of nodes for the minimum error was selected. Better results were obtained when using hyperbolic tangent functions in the hidden and output layers, instead of logistic transfer and linear transfer functions.

Feedforward Backpropagation (FFBP):

FFBP is a type of artificial neural network where information flows in one direction, from input to output layers. It consists of an input layer, one or more hidden layers, and an output layer. Each neuron is connected to every neuron in the subsequent layer. FFBP is suitable for making predictions when there is no temporal dependency among the input data. It excels in tasks such as image recognition, where each input can be treated independently. FFBP is limited in predicting time-series or sequential data since it doesn't inherently capture temporal dependencies.

Recurrent Neural Network (RNN):

RNNs are designed to capture sequential information by introducing connections between neurons that form directed cycles. Each neuron has a hidden state that retains information about previous inputs, allowing it to capture temporal dependencies. RNNs are well-suited for sequential prediction tasks, such as time series forecasting, natural language processing, and video analysis. They can effectively model sequences of data and make predictions based on the context provided by previous inputs. RNNs can suffer from the vanishing or exploding gradient problem, limiting their ability to capture long-term dependencies. Additionally, traditional RNNs may struggle with capturing very long-term dependencies due to their architecture.

Elman Network:

Elman networks are a type of RNN with a simple architecture. They consist of an input layer, a hidden layer with recurrent connections, and an output layer. The hidden layer maintains a state that represents information from previous time steps. Elman networks are suitable for tasks requiring short-term memory, such as predicting the next value in a time series based on recent observations. They can capture immediate dependencies between consecutive inputs. While Elman networks are effective for capturing short-term dependencies, they may struggle with capturing long-term dependencies due to limitations in their architecture.

Nonlinear Autoregressive with exogenous inputs (NARX):

NARX models combine elements of feed forward neural networks with time-delayed feedback. They have both feed forward and feedback connections, allowing them to capture dynamic dependencies in data. NARX models are suitable fo predicting time series with complex temporal dependencies. By incorporating feedback connections, they can capture the effects of past inputs and outputs on future predictions. NARX models offer a more flexible architecture compared to traditional feed forward and recurrent networks. They are capable of capturing both short-term and long-term dependencies in data, making them well-suited for a wide range of prediction tasks.

3.2 Software

The software applications used in the present study is MATLAB which is used as a powerful tool and capabilities for utilizing artificial neural network (ANN) models in prediction tasks across various domains. ANN models, inspired by the structure and function of the human brain, are widely used for predictive modeling due to their ability to learn complex patterns and relationships from data. MATLAB's comprehensive suite of functions, toolboxes, and visualization capabilities makes it an ideal platform for developing, training, and deploying ANN models for prediction tasks.

3.3 PHASES OF STUDY

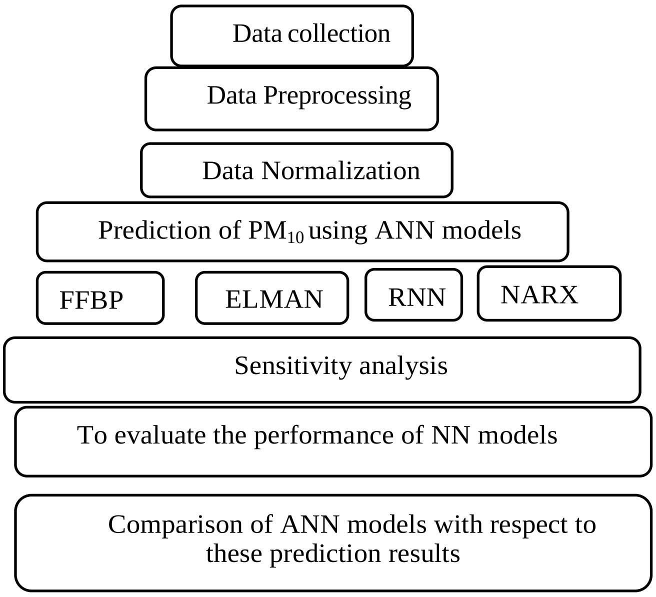

Fig. 2. Flowchart for methodology

The methodology followed includes Data collection, Data preprocessing, Data Normalization, Prediction of PM_{10} using ANN models, Sensitivity analysis, Evaluation of ANN Model Performance, Comparison of ANN Models and Finding the Best Prediction Model.

1. Data Collection:

Daily average PM_{10} data for six years period from 1st January 2018 to 31st December 2023 were collected from CPCB website were used for the study.
Five meteorological variables namely Wind speed, Wind direction, Atmospheric Temperature, Relative humidity,

arometric pressure were considered as influencing parameters for PM_{10} concentrations. The data relating to all the five meteorological parameters for six years period were used for the study. The data was collected from CPCB Website.

The concise dataset underwent random partitioning into separate subsets (Comrie, 1997; Kolehmainen et al., 2001; Perez and Reyes, 2002) to facilitate the development and evaluation of models. The neural networks were trained using the majority of the dataset (3/4), while the remaining cases were evenly distributed into validation and test sets. Early stopping regularization was implemented on the validation set during network training to enhance generalization capabilities. The independent test set remained untouched throughout the training process and was exclusively utilized for statistically comparing the performance of different models. This method, known as split-sample or hold-out validation, is widely employed in numerous relevant research studies utilizing early stopping to mitigate over fitting (Gardner and Dorling, 1999; Gardner and Dorling, 2000; Chaloulakou et al., 2003b, c).

2. Data Preprocessing:

Missing PM_{10} data were estimated by simple interpolation before normalization.

3. Data Normalization

Normalization is a process used to scale numeric data to a standard range, usually between -1 and +1. It helps in comparing different features with different scales and also aids machine learning algorithms in converging faster. There are various normalization techniques, In present work the common formula for min-max normalization is used. Which scales data to the range [-1, +1]. The formula is given below

$X_{new}=(X-X_{max})/(X_{max}-X_{min})$……….(1)

Where X_{max} = Maximum value of the parameter,

X_{min} = Minimum value of the parameter

X_{new}= Normalized value of the parameter

This formula ensures that the minimum value in the dataset is scaled to -1 and the maximum value is scaled to 1, while other values are scaled proportionally in between.

4: Prediction of PM_{10} using ANN Models

Four different artificial neural network (ANN) models were used namely Feed forward Back Propagation (FFBP), ELMAN Neural Network, Recurrent Neural Network (RNN), and Non-linear Autoregressive with Exogenous input (NARX), were used to predict PM_{10} concentrations based on the analyzed data.

5: Sensitivity Analysis

Sensitivity analysis was conducted to evaluate the predicted results using the ANN models. This involves finding the Correlation Coefficient (R) and Mean Squared Error (MSE) for the predicted results to actual results, which are important metrics for assessing the accuracy and reliability of the models.

The predicted results using different neural networks were analyzed using sensitivity analysis. The parameters selected for the comparison were:

Correlation Coefficient (R): Correlation is a statistical association it refers to how a pair of variables is linearly related. Correlation Coefficient (R) was calculated by the following Eq.

$$R = \frac{\Sigma(Oc-Mc)(Oe-Me)}{\sqrt{\Sigma(Oc-Mc)^2+(Oe-Me)^2}} \quad \text{…………………}(2)$$

Where, Oc = observed concentrations,

Oe = estimated concentrations,

Mc = Mean of observed concentration,

Me = mean of estimated concentration.

Mean Squared Error (MSE): It measures the average of the squares of the errors. The equation used for calculation of MSE is as follows:-

$$MSE=\frac{1}{N}\Sigma(Oc-Oe)^2 \text{…………………… } (3)$$

Where Oc = observed concentrations,

Oe = estimated concentrations,

N = Total number of data sets.

6: Evaluation of ANN Model Performance

The performance of the ANN models was evaluated to assess their effectiveness in predicting PM10 concentrations. Assessing the models' ability to capture the underlying patterns in the dataset.

7: Comparison of ANN Models

The ANN models were compared with respect to their prediction results. This step involved analyzing the strengths and weaknesses of each model and identifying the variations in their predictive performance.

8: Finding the Best Prediction Model

Based on the comparison and evaluation, the study aimed to identify the best prediction model among the ANN models for forecasting PM_{10} concentrations. This step likely involved selecting the model that demonstrated the highest accuracy and reliability in predicting PM_{10} levels.

The study involved assessing the performance of several Neural Network models, including FFBP, Elman Network, RNN, and NARX, for four air quality monitoring stations they are discussed with results below.

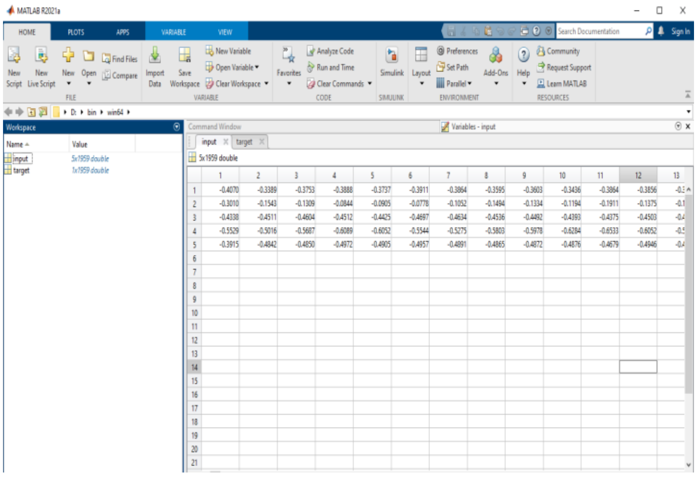

Fig. 3. Window Showing Workspace with Input and Target data

Creating workspace with Input and Target Data is shown in figure this is done to import the data from workspace to neural network tool box. Before we feed input and target data into workspace it has to be normalized between -1 to +1. Here we can see in the above figure that five input variables of Normalized meteorological data and Normalized PM10 concentration data as target variable are feed into the workspace.

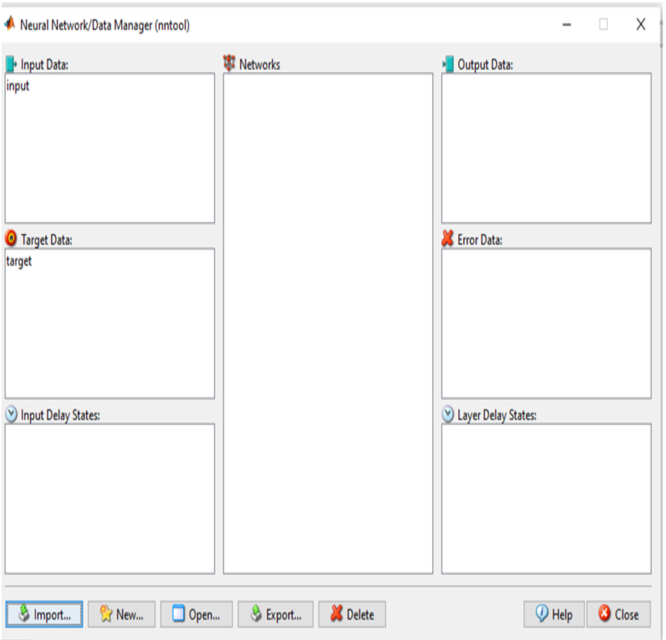

Fig. 4.window showing imported data of input and target data to nntool box

In neural network tool box, import Input and target data into it and then click on New then create a network type which we are going to use as models in our research work. So this as done for all four monitoring stations data separately.

4.0 RESULTS AND DISCUSSIONS

The results for the four different models for four sites are discussed one by one below at first

a) NAME OF THE MONITORING STATION: BAPUJI NAGAR

i) Feed forward Back propagation neural network

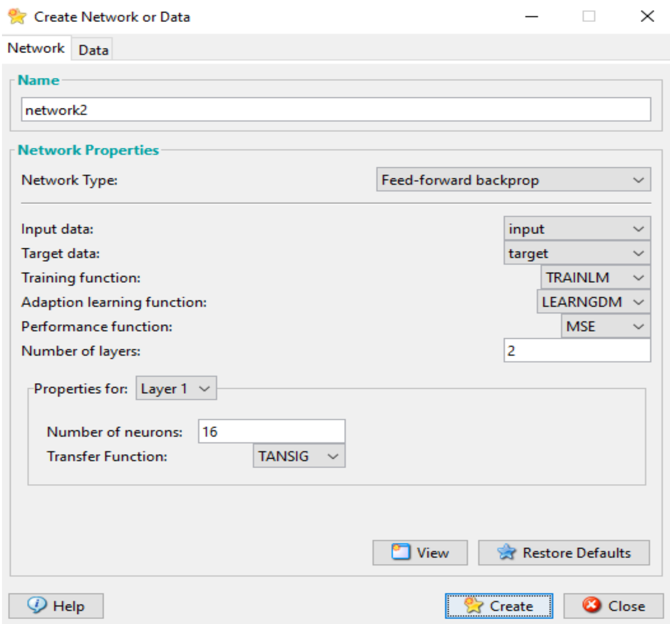

Fig. 5. Showing the FFBP network properties

Here after creating network there opens an network properties window where we used to select network type that means which model we are going to use and then we should select input and target data and TRAINLM as training function and LEARNGDM as adaption learning function and performance as MSE and transfer function as TANSIG (tan sigmoid function) and number of neurons are selected based on trial and error method which neuron gives better result that as been selected. It has been done based on sensitivity analysis that is R and MSE values.

For all the models it has to be done in the same way the only thing that need to be changed is that the Network type and the number of neurons for which it gives better result.

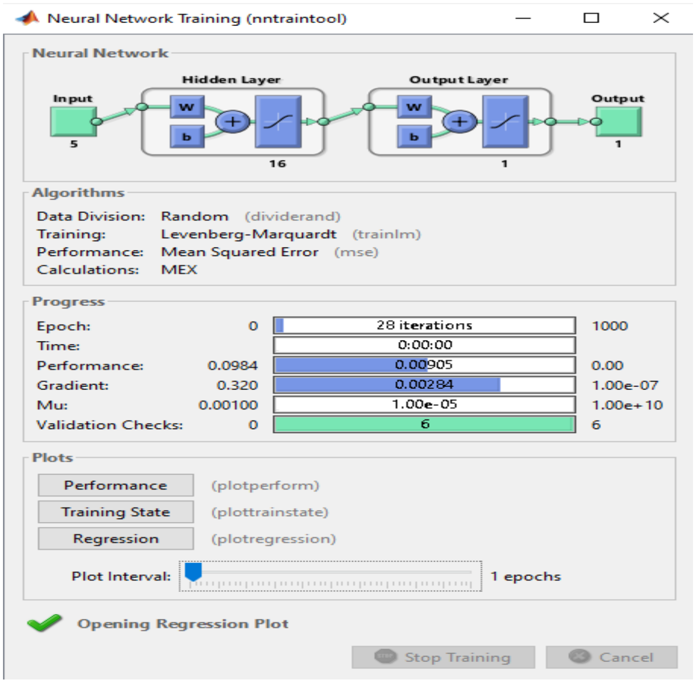

Fig. 6. Showing performance window

Here the random data division and Levenberg marquardt training function as been used and also progress of the algorithm where it stopped the epochs , time taken, gradient, performance, validation checks etc are shown in the figure and also shows the plots of performance and regression where we can find the accuracy of the prediction model. And also we can see the architecture of the model where we used five input variables and one target variables along with the number of neurons in the hidden layer. The window obtained will be same for all the models for all the stations only the change is that the performance of each models.

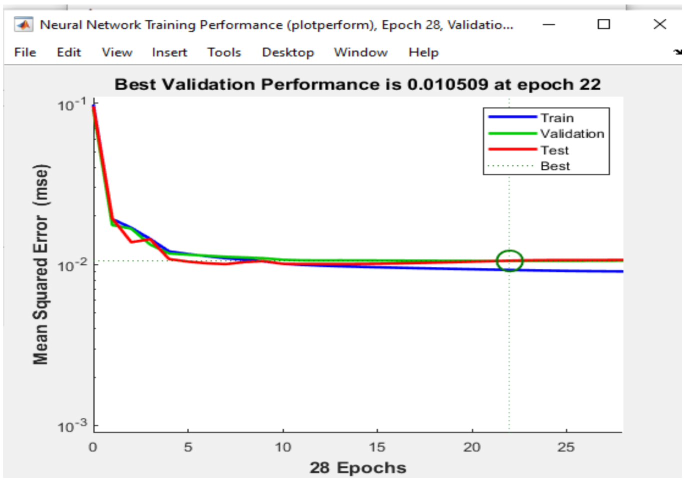

Fig. 7. Graph shows the best validation performance of FFBP with MSE value 0.010509

Here the graph shows mean squared error as 0.010509 for the performance of FFBP for 28 iterations and in the graph we can see that the line of training validation and testing are gradually decreased this means that it was learning like the above we get graphs for MSE values for all stations for different models by subtracting actual data from predicted data and squaring the obtained value, summing up the obtained value and dividing by number of output or target values this has to be done for all stations for four different models.

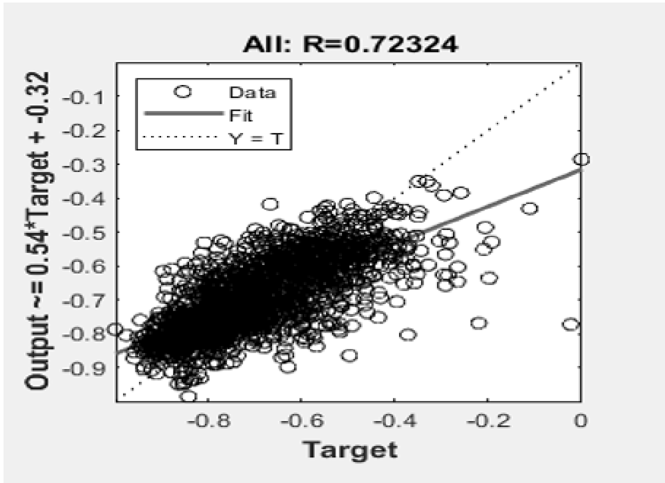

Fig. 8. Graph shows the R value of FFBP with value 0.72324

Here the graph shows overall R value for training, validation and testing as 0.72324 this is obtained by determining the correlation between actual PM_{10} concentration and predicted PM_{10} concentration like this way it has to be done for all the models for four stations so based on this R value and earlier mentioned MSE values we can able to determine the performance of the models.

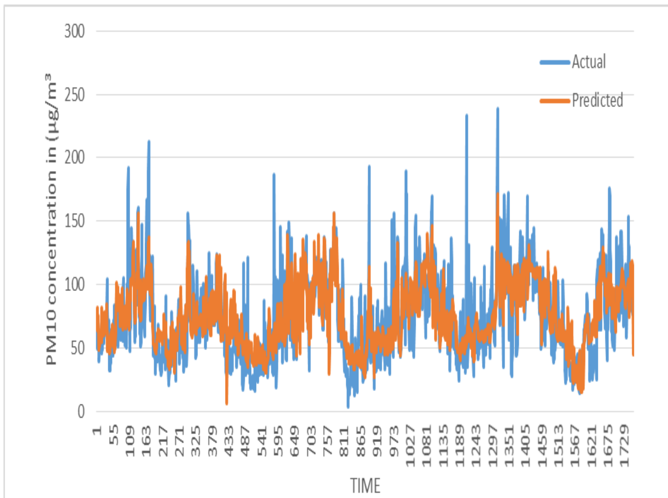

Fig. 9. Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of FFBP network was obtained for 16 number of neurons with R value 0.72324 and MSE value 0.010509. In actual data the maximum PM_{10} concentration was 238.66µg/m^3 and minimum was 3.42µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 171.26 µg/m^3 and minimum was 6.618892 µg/m^3.

ii) ELMAN Neural network

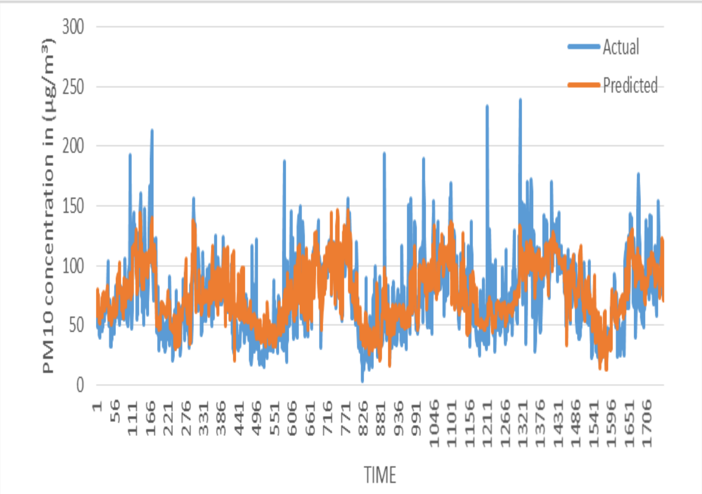

Fig. 10. Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of ELMAN network was obtained for 14 number of neurons with R value 0.71951 and MSE value 0.009175. In actual input data the maximum PM_{10} concentration was 238.66 µg/m^3 and minimum was 3.42 µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 146.7433µg/m^3 and minimum was 12.77304µg/m^3.

iii) Recurrent Neural network (RNN)

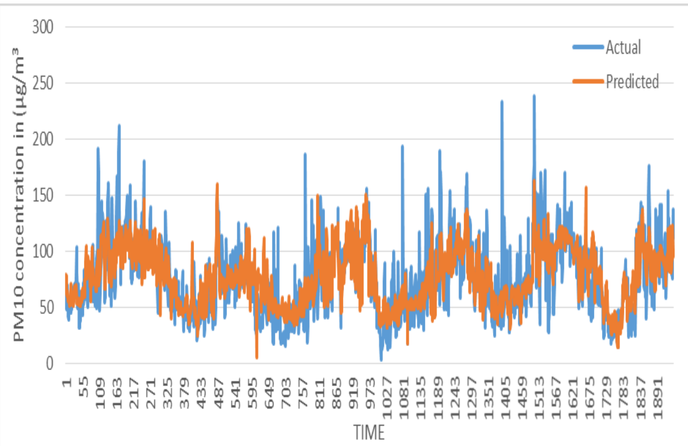

Fig. 11. Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of RNN network was obtained for 15 number of neurons with R value 0.73031 and MSE value 0.008962. In actual input data the maximum PM_{10} concentration was 238.66 µg/m^3 and minimum was 3.42 µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 162.7514µg/m^3 and minimum was 6.003182µg/m^3.

iv) Nonlinear Autoregressive network with exogenous Inputs (NARX)

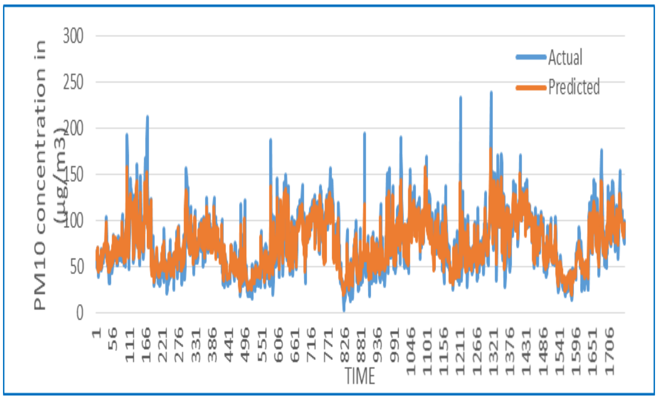

Fig. 12 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of NARX network was obtained for 16 number of neurons with R value 0.82174 and MSE value 0.0070605. In actual input data the maximum PM_{10} concentration was 238.66 µg/m^3 and minimum was 3.42 µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 177.1803µg/m^3 and minimum was 19.26022µg/m^3.so this model gives PM_{10} concentration nearly to actual measured PM_{10}.

b) NAME OF THE MONITORING STATION: HEBBAL

i) Feed forward Back propagation neural network

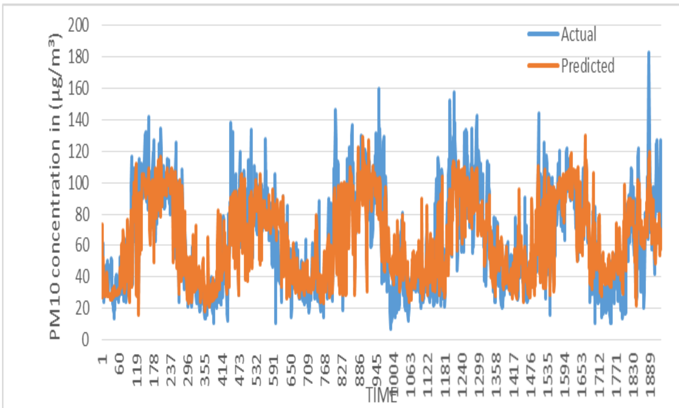

Fig. 13 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of FFBP network was obtained for 13 number of neurons with R value 0.78264 and MSE value 0.014841. In actual input data the maximum PM_{10} concentration was 182.82µg/m^3 and minimum was 7.32µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 129.5209µg/m^3 and minimum was 15.76931µg/m^3.

ii) ELMAN Neural network

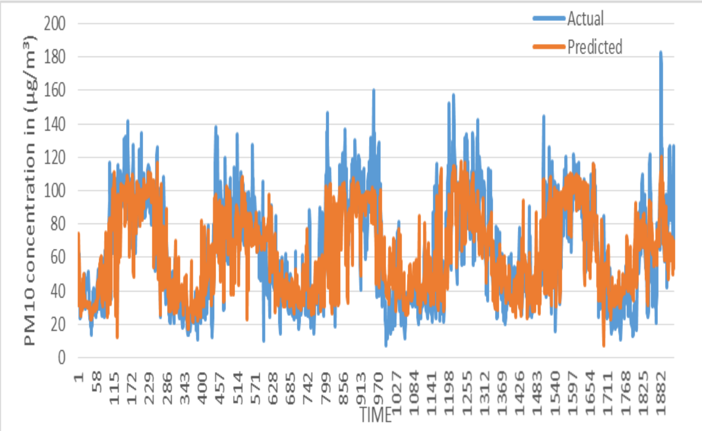

Fig. 14 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of ELMAN network was obtained for 15 number of neurons with R value 0.787782 and MSE value 0.012606. In actual input data the maximum PM_{10} concentration was 182.82µg/m^3 and minimum was 7.32µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 119.9033µg/m^3 and minimum was 7.690726µg/m^3.

iii) Recurrent Neural network (RNN)

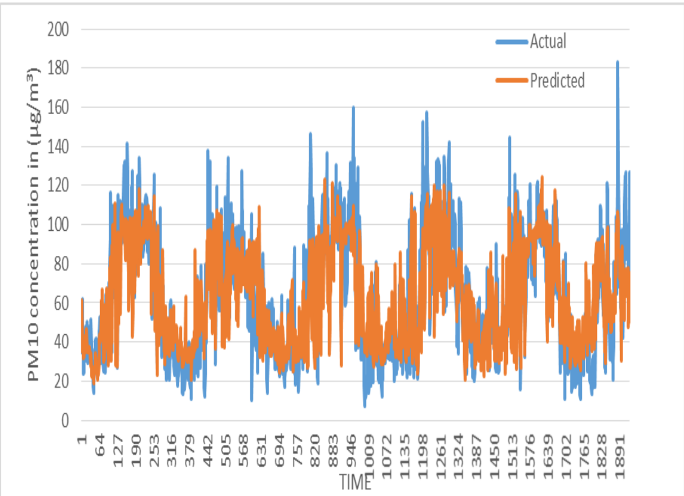

Fig. 15 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of RNN network was obtained for 12 number of neurons with R value 0.79093 and MSE value 0.010779. In actual input data the maximum PM_{10} concentration was 182.82µg/m^3 and minimum was 7.32µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM10 obtained was 124.4375µg/m^3 and minimum was 18.72366µg/m^3.so this model gives PM_{10} concentration nearly to actual measured PM_{10}.

iv) Nonlinear autoregressive network with exogenous Inputs (NARX)

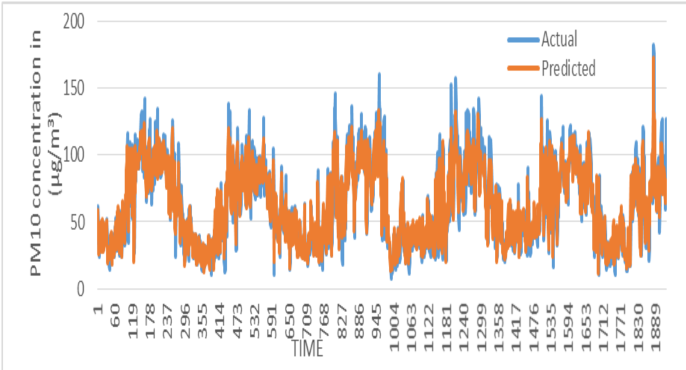

Fig. 16 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of NARX network was obtained for 12 number of neurons with R value 0.84914 and MSE value 0.008126. In actual input data the maximum PM_{10} concentration was 182.82µg/m^3 and minimum was 7.32µg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 173.1163µg/m^3 and minimum was 11.25515µg/m^3.so this model gives PM_{10} concentration nearly to actual measured PM_{10}.

C) NAME OF THE MONITORING STATION: JAYANAGAR

i) Feed forward Back propagation neural network

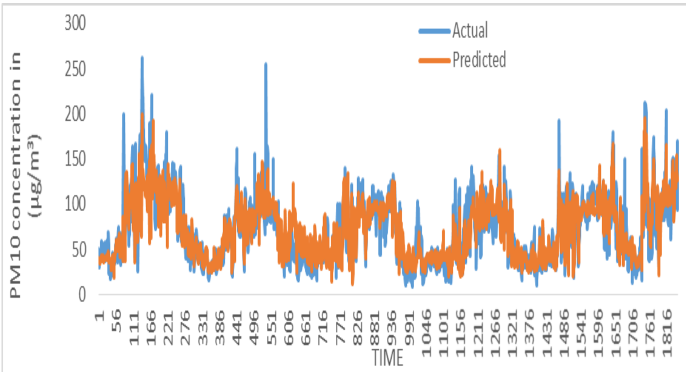

Fig. 17. Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of FFBP network was obtained for 19 number of neurons with R value 0.81314 and MSE value 0.007445. In actual input data the maximum PM_{10} concentration was 261.88μg/m^3 and minimum was 9.52μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 199.2321μg/m^3 and minimum was 12.54594μg/m^3.

ii) ELMAN Neural network

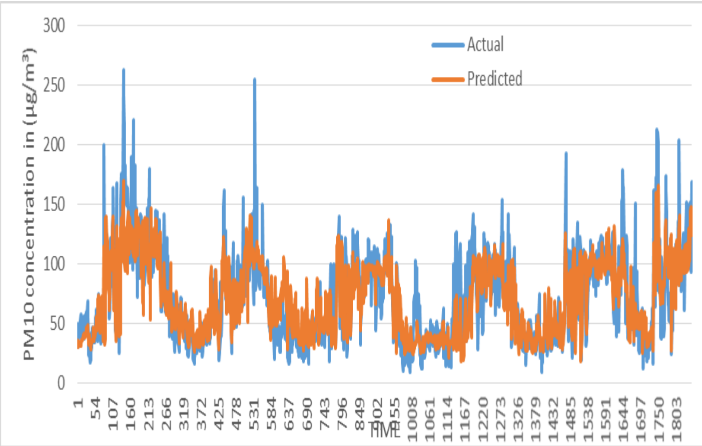

Fig. 18 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of ELMAN network was obtained for 17 number of neurons with R value 0.80989 and MSE value 0.006919. In actual input data the maximum PM_{10} concentration was 261.88μg/m^3 and minimum was 9.52μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 169.8613μg/m^3 and minimum was 19.2103μg/m^3.

iii) Recurrent Neural network

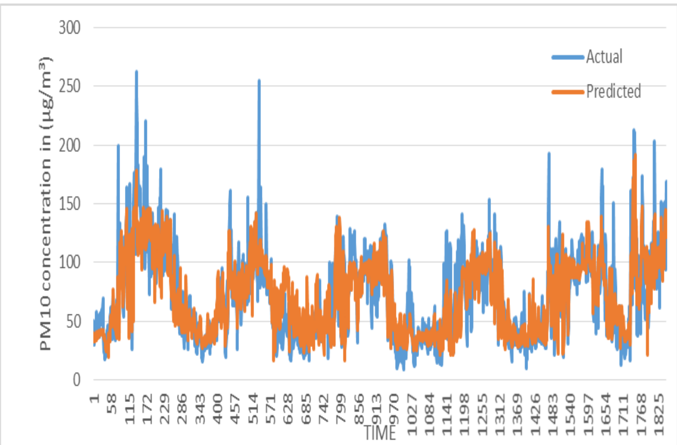

Fig. 19 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of RNN network was obtained for 20 number of neurons with R value 0.823453 and MSE value 0.0080737. In actual input data the maximum PM_{10} concentration was 261.88μg/m^3 and minimum was 9.52μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 191.7104μg/m^3 and minimum was 16.62357μg/m^3.

iv) Nonlinear autoregressive network with exogenous Inputs (NARX)

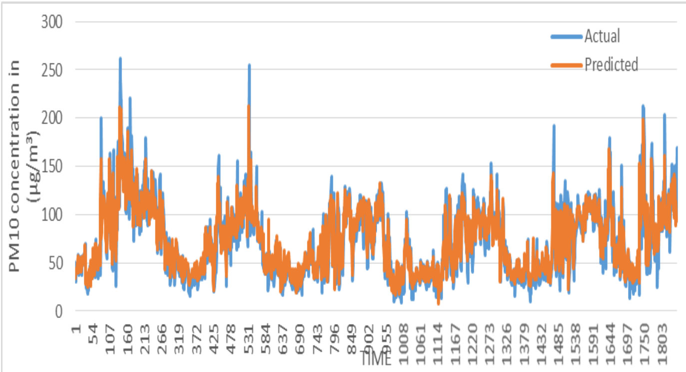

Fig. 20. Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of NARX network was obtained for 20 number of neurons with R value 0.87773 and MSE value 0.006025. In actual input data the maximum PM_{10} concentration was 261.88μg/m^3 and minimum was 9.52μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 212.3756μg/m^3 and minimum was 7.94313μg/m^3.so this model gives PM_{10} concentration nearly to actual measured PM_{10}.

d) NAME OF THE MONITORING STATION: HOMBEGOWDA NAGAR

i) Feed forward Back propagation neural network

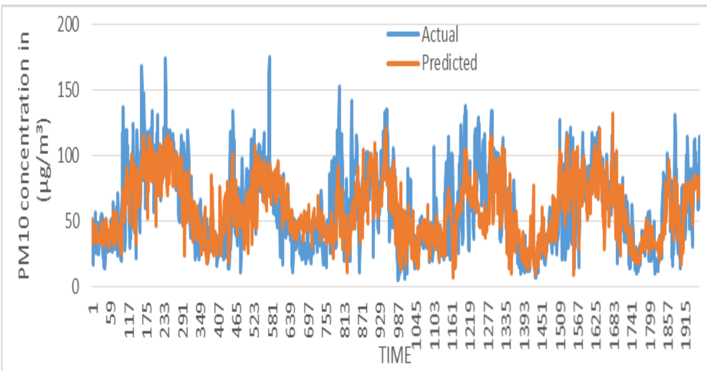

Fig. 21 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of FFBP network was obtained for 17 number of neurons with R value 0.7456 and MSE value 0.015902. In actual input data the maximum PM_{10} concentration was 174.92μg/m^3 and minimum was 5.65μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 131.4208μg/m^3 and minimum was 6.94414μg/m^3.

ii) ELMAN Neural network

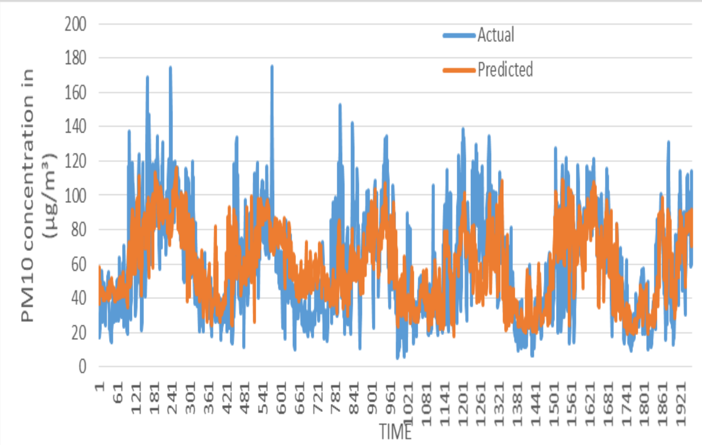

Fig. 22 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of ELMAN network was obtained for 16 number of neurons with R value 0.71411 and MSE value 0.014244. In actual input data the maximum PM_{10} concentration was 174.92μg/m^3 and minimum was 5.65μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 116.3685μg/m^3 and minimum was 18.44614μg/m^3.

iii) Recurrent Neural network

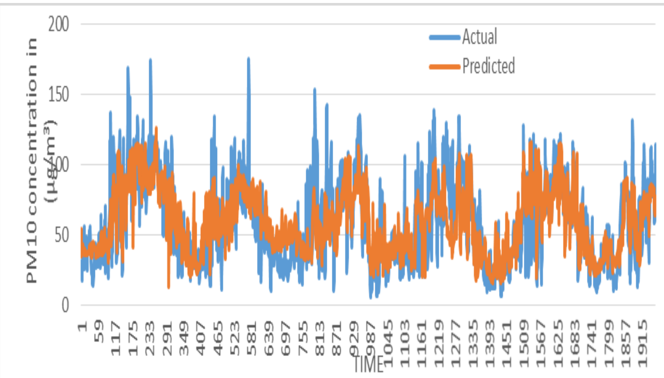

Fig. 23 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of RNN network was obtained for 15 number of neurons with R value 0.73513 and MSE value 0.013311. In actual input data the maximum PM_{10} concentration was 174.92μg/m^3 and minimum was 5.65μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 125.9095μg/m^3 and minimum was 13.54332μg/m^3.

iv) Nonlinear autoregressive network with exogenous outputs (NARX)

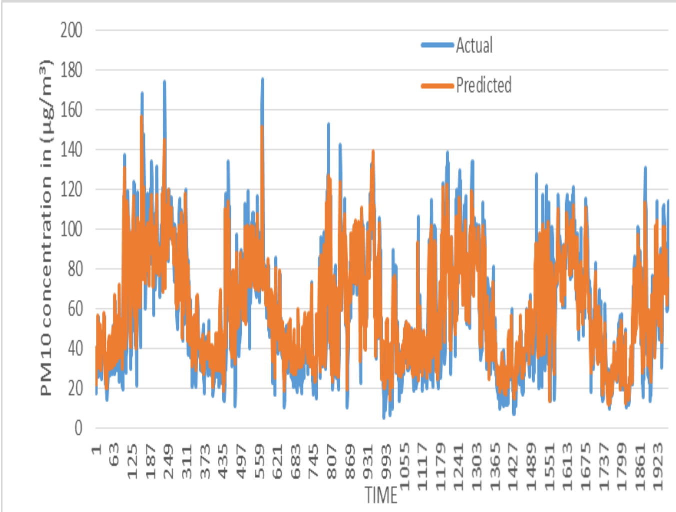

Fig. 24 Graph shows actual and predicted concentration of PM_{10}

Figure shows the actual and predicted concentration of PM_{10} Here the best performance of NARX network was obtained for 16 number of neurons with R value 0.88774 and MSE value 0.008094. In actual input data the maximum PM_{10} concentration was 174.92μg/m^3 and minimum was 5.65μg/m^3 it can also be shown in the figure and for predicted data we get maximum PM_{10} obtained was 156.3969μg/m^3 and minimum was 12.00921μg/m^3.so this model gives PM_{10} concentration nearly to actual measured PM_{10}.

Notably, it was consistently found that employing the Tan sigmoid activation function yielded the most favorable results across all monitored stations.

4.1 Comparative evaluation of the models

A comprehensive breakdown of the outcomes for each neural network at every designated stations is outlined in Table 2.

Table 2 Values of R and MSE for each network for selected stations

Networks	Optimum neurons	R	MSE
	BAPUJI NAGAR		
FFBP	16	0.72324	0.010509
ELMAN	14	0.71951	0.009175
RNN	15	0.73031	0.008962
NARX	16	0.82174	0.007060
	HEBBAL		
FFBP	13	0.78264	0.014841
ELMAN	15	0.78778	0.012606
RNN	12	0.79093	0.010779
NARX	12	0.84914	0.008126
	JAYANAGARA		
FFBP	19	0.81314	0.007445
ELMAN	17	0.80989	0.006919
RNN	20	0.82345	0.008073
NARX	20	0.87773	0.006025
	HOMBEGOWDA NAGARA		
FFBP	17	0.74560	0.015902
ELMAN	16	0.71411	0.014244
RNN	15	0.73513	0.013311
NARX	16	0.88774	0.008094

In Table 2, the Mean Squared Error (MSE) and R (correlation coefficient) values are presented for selected stations for different neural networks. The stations with the highest R value of 0.88774 and the lowest MSE value of 0.0080947 is obtained for HombegowdaNagar station. These results are graphically depicted in Figures 25 and 26. However, the Elman Network exhibits comparatively poor performance across all sites, with an R value of 0.714113 and MSE value of 0.014244 for HombegowdaNagar. Similarly, the Feed forward Back propagation (FFBP) Network performs inadequately for Bapuji Nagar, with an R value of 0.72324 and MSE value of 0.010509. This diminished performance of the Elman and FFBP networks can be attributed to their high sensitivity to architectural configurations and parameter choices.

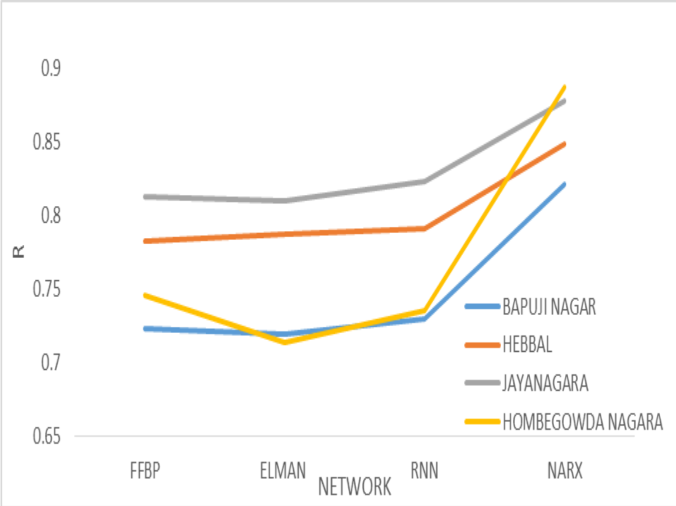

Fig. 25 R values

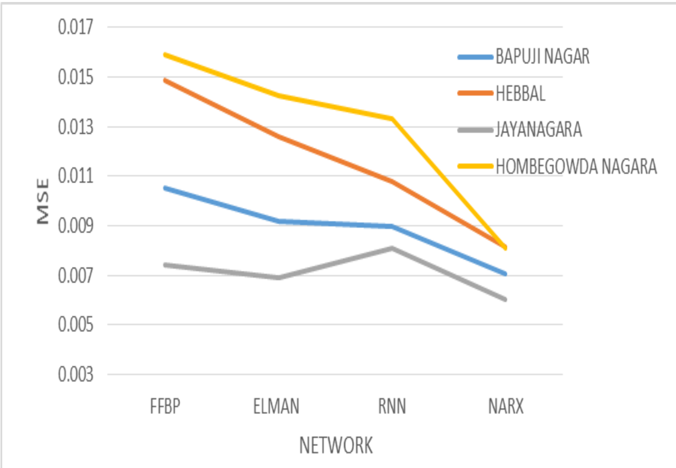

Fig. 26 MSE values

5.0 CONCLUSIONS

The study focused on predicting particulate matter (PM_{10}) concentration in Bengaluru using artificial neural networks, specifically NARX, RNN, FFBP, and ELMAN models. Data on PM_{10} concentration and meteorological parameters were collected from four stations in Bengaluru. The results indicated that the NARX network outperformed the other neural network models in predicting PM_{10} concentration at these sites. This finding underscores the significance of accurate prediction models for PM_{10} concentration in addressing air pollution in Bengaluru. The comparisons of different ANN models provide insights into the strengths and weaknesses of each model, offering valuable information on their effectiveness in predicting air pollution levels. Overall, the research contributes to the understanding of the potential of artificial neural networks in predicting PM_{10} concentration and emphasizes the importance of robust prediction models in combating air pollution in urban areas like Bengaluru.

Utilizing meteorological parameters as input and pollutant concentrations, notably PM_{10}, as target data, diverse neural network models were executed. The precision of these predictive models renders them valuable as early warning systems for governmental authorities. By leveraging these models, governments can formulate or adapt policies aimed at enhancing air quality within specific regions. Moreover, such models serve to raise awareness among local residents regarding the concerning degradation of air quality.

REFERENCES

Chaloulakou, A., Saisana, M., Spyrellis, N., 2003b. Comparative assessment of neural networks and regression models for forecasting summertime ozone in Athens. The Science of the Total Environment 313, 1–13.

Chaloulakou, A., Grivas, G., Spyrellis, N.: Neural network and multiple regression models for PM10 prediction in Athens: a comparative assessment. J. Air Waste Manage. Assoc. 53(10),1183–1190 (2003).

Comrie, A.C., 1997. Comparing neural networks and regression models for ozone forecasting. Journal of the Air & Waste Management Association 47, 653–663.

Gardner, M.W., Dorling, S.R., 1999. Neural network modeling and prediction of hourly NOx an NO2 concentrations in urban air in London. Atmospheric Environment 31, 709–719.

Gardner, M.W., Dorling, S.R., 2000. Statistical surface ozone models: an improved methodology to account for non-linear behaviour. Atmospheric Environment 34, 21–34.

Ghazi, S., Khadir, M.T.: Recurrent neural network for multi-steps ahead prediction of PM10 concentrations. J. Autom. Syst. Eng. 3, 13–21 (2009)

Gündo˘gdu, S.: Comparison of static MLP and dynamic NARX neural networks for forecasting of atmospheric PM10 and SO2 concentrations in an industrial site of Turkey. Environ. Forensics 21, 1–12 (2020)

Gurjar, B.R.: Khaiwal Ravindra and Ajay Singh Nagpur, Air pollution trends over Indian
Megacities and their local-to-global implications. Atmos. Environ. 142, 475–495 (2016).

Jiang, D., Zhang, Y., Xiang, H., Zeng, Y., Tan, J., Shao, D.: Progress in developing an ANN model for air pollution index forecast. Atmos. Environ. 38(40), 7055–7064 (2004).

Kolehmainen, M., Martikainen, H., Ruuskanen, J., 2001. Neural networks and periodic components used in air quality forecasting. Atmospheric Environment 35, 815–825.

Li, X., Peng, L., Yuan, H., Shao, J., Chi, T.: Deep learning architecture for air quality
Predictions. Environ. Sci. Pollut. Res. 23(22), 22408–22417 (2016).

Marjovi, A., Arfire, A., Martinoli, A.: High-resolution air pollution maps in urban environments using mobile sensor networks. In: International Conference on Distributed Computing in Sensor Systems, Fortaleza, pp. 11–20 (2015).

Perez, P., Reyes, J., 2002. Prediction of maximum of 24-h average of PM10 concentrations 30h in advance in Santiago, Chile. Atmospheric Environment 36, 4555–4561.

Wang, D., Wei, S., Luo, H., Yue, C., Grunder, O.: A novel hybrid model for air quality index forecasting based on two-phase decomposition technique and modified extreme learning machine. Sci. Total Environ. 580, 719–733 (2017).

https://www.afro.who.int/health-topics/air-pollution

https://www.thehansindia.com/karnataka/bengaluru-ranks-6th-among-10-most-polluted-cities-755086?infinitescroll