Forecasting PM_{10} Concentrations Using Artificial Neural Network in Imphal City

Nongthombam Premananda Singh*[1]
[1]Department of Civil Engineering, Manipur Institute of Technology, Imphal, India

Romesh Laishram[2]
[2]Department of Electronics and Communication Engineering, Manipur Institute of Technology, Imphal, India

Corresponding Author:- Nongthombam Premananda Singh*[1]

Abstract:- In this study, a forecasting system is developed for predicting PM_{10} levels in Imphal City over the next three days (+1, +2, and +3 days) using artificial neural networks (ANN). The experimental findings indicate that the ANN model can achieve reasonably accurate predictions of air pollutant levels. Moreover, optimizations in model performance are explored through variations in input parameters and experimental setups. Initially, predictions for each of the +1, +2, and +3 days are made independently using the same training dataset. Subsequently, cumulative predictions for +2 and +3 days are generated using previously predicted values from preceding days, yielding improved prediction accuracy. Additionally, the study identifies the optimal size of the training dataset, determining that using data spanning 3 to 15 past days yields the minimum error rates in predicting pollutant concentrations. Finally, the investigation includes the consideration of days-of-week as an input parameter, which enhances forecast accuracy noticeably.

Keywords:- *Air Pollution, Artificial Neural Network, Forecasting, Modelling Technique, Particulate Matter.*

I. INTRODUCTION

Air pollution remains a pressing global environmental issue in major cities (Akkoyunlu et al., 2003; Karaca et al., 2004), significantly impacting human health (Elbir et al., 2000; Tayanc et al., 2000; Dimitrou et al., 2013). Industrial and traffic activities are primary sources of air pollutants such as PM_{10}, SO_2, and NO_2, which contribute significantly to urban air quality degradation. Exceeding permissible limits of these pollutants can lead to both short-term and chronic health problems (Kunzli et al., 2000), with more deaths attributed to poor air quality than to automobile accidents (Deleawe et al., 2010). Prolonged exposure in urban areas increases the risks of asthma, respiratory diseases, cardiovascular ailments, cancer, and mortality (Monteiro et al., 2005). Consequently, effective urban air quality management and predictive systems are essential for anticipating pollution levels and implementing timely control measures. Such systems play a crucial role in alerting healthcare professionals, traffic regulators, and environmental managers to minimize adverse impacts.

While statistical methods have traditionally been used for air quality prediction, they often require extensive historical data and struggle with short-term forecasts (Gardner and Dorling, 1999). Linear regression, although popular, may underperform with random and nonlinear data processes. This limitation has led to the emergence of artificial neural networks (ANN) as superior alternatives, especially for analyzing nonlinear processes (Karaca et al., 2005). ANN models exhibit reasonable accuracy across various time scales in predicting pollutant concentrations (Athanasiadis et al., 2005). They excel in handling complex, nonlinear relationships within datasets and outperform traditional statistical approaches (Kolehmainen et al., 2001; Kukkonen et al., 2003). Literature suggests that ANN techniques can yield reliable estimates by identifying intricate patterns that evade simple mathematical formulas or predefined processes (Rumelhart et al., 1986). Employing the feed-forward neural network structure is common, enabling effective recognition of complex patterns and problem-solving in the presence of noisy datasets (Hertz et al., 1995). Combining ANN with deterministic modeling enhances overall performance capabilities (Fausett et al., 1994).

Recent years have witnessed successful applications of neural network models in atmospheric pollution modeling, including specific applications to air quality studies (Boznar et al., 1993; Gardner and Dorling, 1999a; Chaloulakou et al., 2003). Unlike traditional models, ANN does not require prior assumptions about data distribution, making it adaptable for modeling highly nonlinear relationships and effectively generalizing with new datasets.

II. METHODOLOGY

The aim of the paper is to developed a forecasting model using Artificial Neural Networks (ANN) using various meteorological variables for forecasting PM_{10} in Imphal city. The paper is organized as to develop an Air Pollutant Forecasting System (APFS) which consists of two modules: (a) data collection, and (b) developing ANN model using set of experiments on observed data with various models approaches.

➢ *Artificial Neural Network (ANN)*

Artificial Neural Networks (ANNs) are computational systems modeled after biological neural networks, comprising interconnected processing units called neurons.

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These neurons dynamically process information in response to external inputs (Karaca et al., 2006; Kandasamy et al., 2013). One prominent architecture within ANNs is the Multilayer Perceptron (MLP), first introduced by Rumelhart in 1986. It typically consists of an input layer to receive data, a hidden layer for complex computations, and an output layer for generating predictions. In this study, a feed-forward ANN was employed to forecast air pollutant concentrations using various meteorological variables. The determination of the optimal number of hidden layers was guided by iterative testing, ranging between 8 and 12 layers, to enhance the network's predictive accuracy.

➢ *Data Collection*

To forecast PM_{10} concentrations in Imphal city, India, daily measurements of pollutant levels and meteorological parameters were conducted at a monitoring station located at 24.8074°N 93.9384°E. The station sits at an average elevation of 786 meters (2,579 ft) above mean sea level (MSL) and is centrally located within Manipur state, serving as its capital. Traffic emissions have emerged as the primary source of air pollution in Imphal due to a significant surge in traffic volume over the past decade.

Meteorological data including temperature (in °C), wind speed (in meters per second), and relative humidity (in %) were gathered from the meteorological station at Manipur Pollution Control Board, Lamphelpat, Imphal city. The dataset used for experiments spans from January 2015 to August 2019. Despite Manipur having sixteen districts, only Imphal was selected for this study due to sparse air pollution data in other regions. Many districts experience data gaps, particularly during holidays and weekends, resulting in missing data that constitutes approximately 10% of the overall PM_{10} dataset for Imphal city. To mitigate this, missing data points were replaced using the average values from the nearest two days. However, this data treatment procedure introduces additional error into the forecasting system.

➢ *ANN Model development*

- *NARX Model*

The Nonlinear Autoregressive with Exogenous Inputs (NARX) model is utilized for time series prediction, forecasting future values of a time series *y(t)* based on its own past values and the past values of another time series *x(t)*. This form of prediction is called nonlinear autoregressive with exogenous (external) input, or NARX and can be written as follows:

$$y(t) = f(y(t-1), \ldots, y(t-d), x(t-1), \ldots, (t-d))$$

This approach is crucial in various domains such as economic forecasting (e.g., stock or bond prices using economic indicators like unemployment rates and GDP) and system identification (e.g., modeling dynamic systems in chemical processes, manufacturing, robotics, and aerospace). The standard NARX network architecture comprises a two-layer feedforward structure: a hidden layer with sigmoid activation functions and an output layer with linear activation functions. Tapped delay lines are employed to store previous values of *x(t) and y(t)*. During training, the output *y(t)* is typically fed back into the input through delays. However, to optimize training efficiency, an open-loop architecture can be used where the true output is substituted for the estimated output during training. This approach improves accuracy in feedforward input and simplifies the training algorithm. The default setup includes 10 hidden neurons and 2 delays, adjustable to 4 if training performance is suboptimal.

- *Neural Network Model*

The forecasting model for meteorological and air pollutant conditions employs an Artificial Neural Network (ANN) using a feedforward backpropagation algorithm implemented in MATLAB. The ANN model is structured with four input nodes representing meteorological and air quality data, and ten nodes in a hidden layer (as depicted in Figure 1). Hyperbolic tangent sigmoid functions serve as transfer functions for neurons. The training process utilizes the Levenberg-Marquardt optimization method to adjust weights and biases.

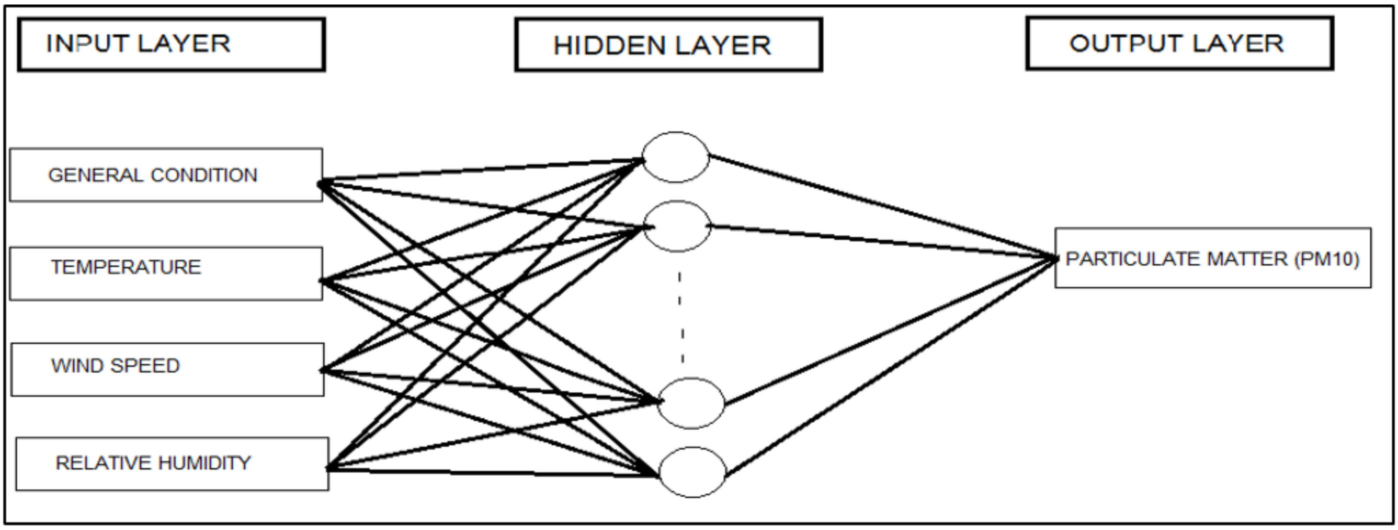

Fig 1 The Artificial Neural Network Model

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The methodology involves testing with different input configurations: 12 inputs for predicting +3 days ahead, 28 inputs for +7 days ahead, and 40 inputs for +10 days ahead forecasting. The number of nodes is selected based on minimizing prediction error, with log-sigmoid transfer functions for input neurons and linear transfer functions for output neurons.

These approaches enable accurate forecasting of air pollutant levels based on current and historical meteorological data, facilitating proactive environmental management and health protection strategies.

III. EXPERIMENT SETUP

In the initial experiment, predictions are made independently for the next three days (+1, +2, and +3 days) using the same training dataset. Subsequently, in the latter part, cumulative predictions for +2 and +3 days utilize previously predicted values from earlier days. Both experiments employ the same neural network architecture.

The objective of the second experiment is to determine the optimal number of past days used in training neural networks to enhance prediction accuracy. In the third experiment, the influence of the day of the week as an input parameter on prediction accuracy is investigated. Error rates are quantified using the Absolute Error (AE), which measures the discrepancy between actual and predicted values. AE is calculated as:

$$AE = |X_a - X_p/X_a|*100 \quad (1)$$

Where, X_a is as observed or measured PM_{10} concentrations, X_p is as predicted PM_{10} concentrations. In this study, Absolute Error (AE) is used to quantify the difference between observed (Xa) and predicted (Xp) PM_{10} concentrations. The pollutant concentrations are categorized into 5 bands or intervals based on the minimum and maximum values in the dataset. These bands provide meaningful interpretations for end users, possibly conveyed through color codes or descriptive labels, without directly disclosing the actual pollutant concentrations. This approach helps in effectively communicating the severity of air pollution levels to stakeholders and decision-makers involved in environmental management and public health initiatives.

IV. RESULTS AND DISCUSSIONS

In this study, the ANN model is employed to forecast PM_{10} concentrations for three different forecasting horizons: three days, seven days, and ten days ahead. The goal is to enhance the accuracy of predicting air pollution parameters by evaluating various neural network models. Typically, similar studies focus on predicting air pollution levels for the next day (tomorrow) due to the inherent difficulty in forecasting further into the future (Kandaswamy et al., 2013). However, this study extends the forecasting horizon to assess longer-term predictions.

The study begins with preprocessing the data to ensure consistency and integrity of the database. Subsequently, the dataset is partitioned into distinct components: training data, training targets, testing data, testing targets, and the network's output. The Artificial Neural Network (ANN) model employed in this research consists of three primary layers: the input layer comprising the training dataset, followed by a hidden layer, and finally an output layer.The ANN is trained using a comprehensive set of input variables, including PM_{10} concentrations over 3 days, 7 days, and 10 days, as well as 24-hour averages of wind speed, air temperature, and humidity. Each node in the input layer connects to nodes in the hidden layer, where signals are processed through activation functions before being transmitted to the output layer to produce predictions. This iterative process continues until the algorithm minimizes the error between predicted outputs and desired targets. Table 1 shows the parameters of the ANN model structure for which the best forecasting results were developed and Table 2 shows the attributes (inputs and outputs) used in ANN model.

Table 1 Parameters of the ANN Model

TEST	PARAMETERS OF THE ANN MODEL		
	ANN model	**Network**	**Transfer function**
1	Forecasting PM_{10} 3 days	12x10x3	logsig
2	Forecasting PM_{10} 7 days	28x10x3	logsig
3	Forecasting PM_{10} 10 days	40x10x3	logsig

Table 2 Attributes (Inputs and Outputs) used in ANN Model

Attribute	Parameters	Unit	Range (Min, Max)	Mean	SD (Std. Dev.)
Input	Temperature	°C	[1; 31.5]	16	5
Input	Humidity	%	[27; 97]	62	43
Input	Wind speed	m/s	[1; 24]	12	8
Output	PM_{10}	µg/m3	[9; 170.95]	90	63

Figure 2 (a), (b) and (c) shows the performance of the ANN model in prediction of PM_{10} concentration in +3 days, +7days and +10 days ahead of time respectively and figure 3 (a), (b) and (c) shows the comparison of predicted and observed PM_{10} concentration in +3 days, +7days and +10 days respectively. While figure 4 (a), (b) and (c) shows the training results of ANN model in +3 days, +7days and +10 days respectively

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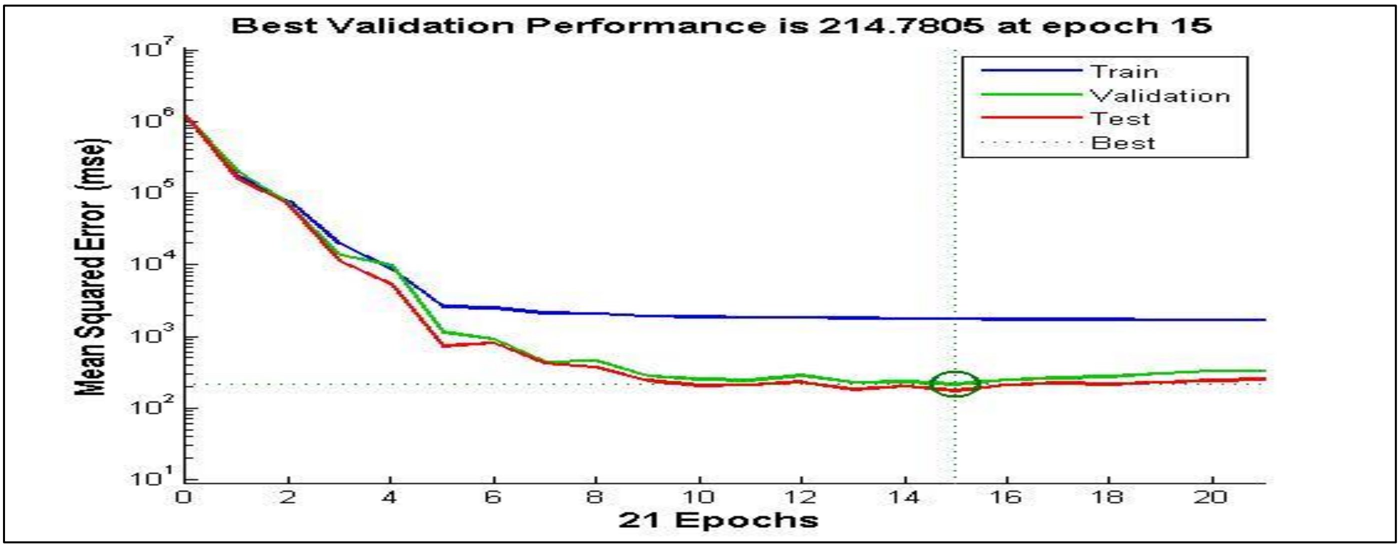
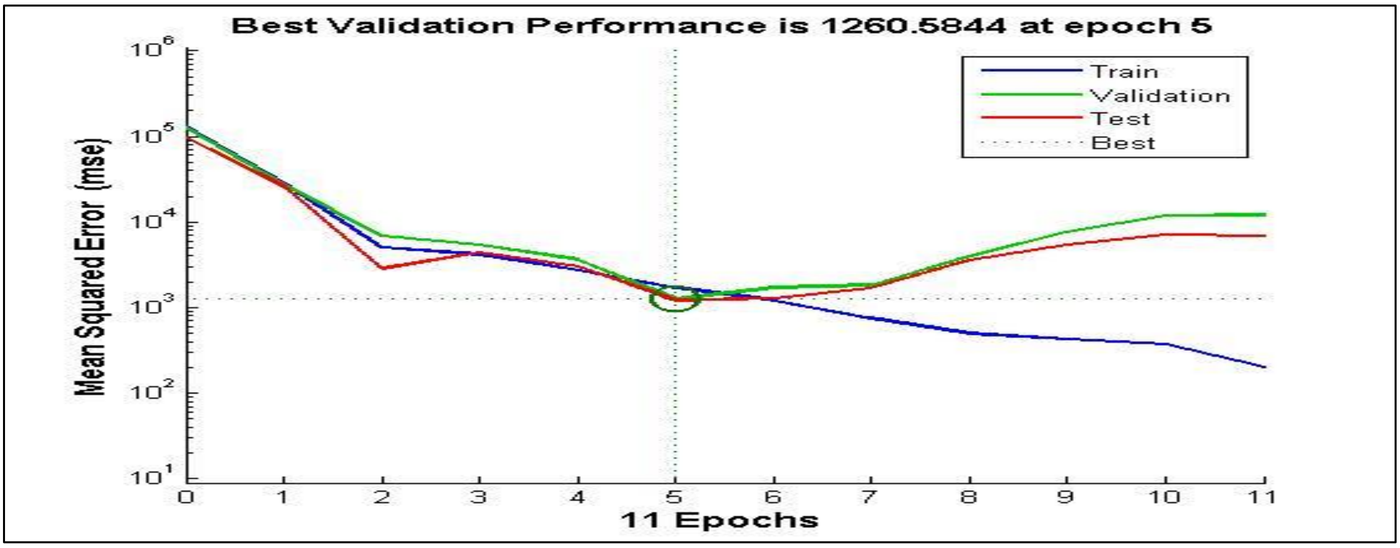


(a)



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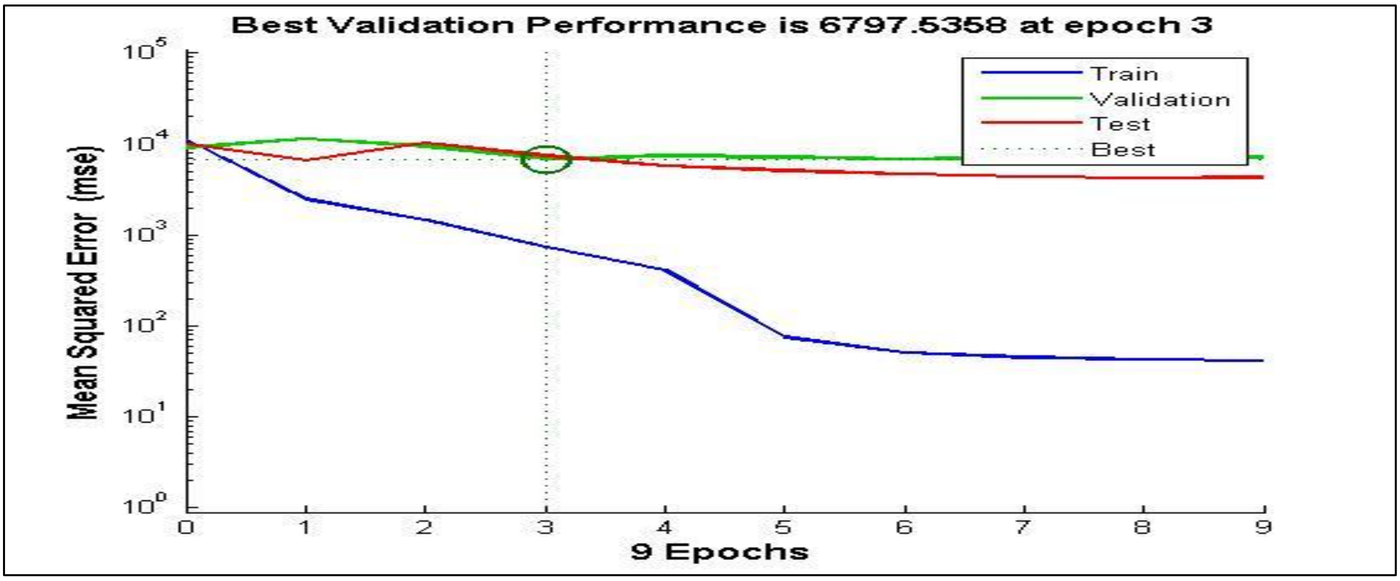

(c)
Fig 2 Performance ANN Model in Predicting PM_{10} Concentration as
First Test Case (a) +3 Days ahead (b) +7 Days and (c) +10 Days

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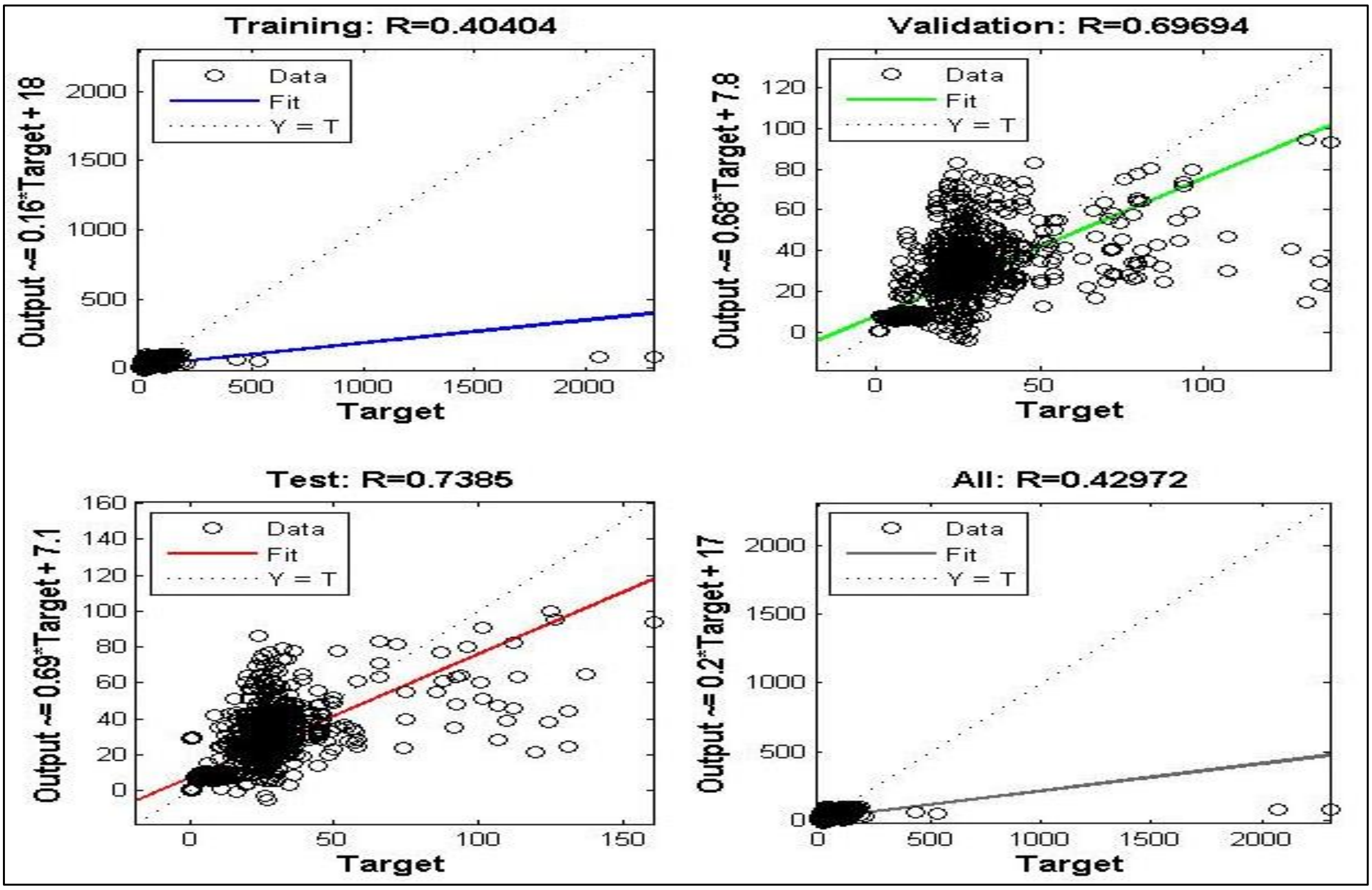
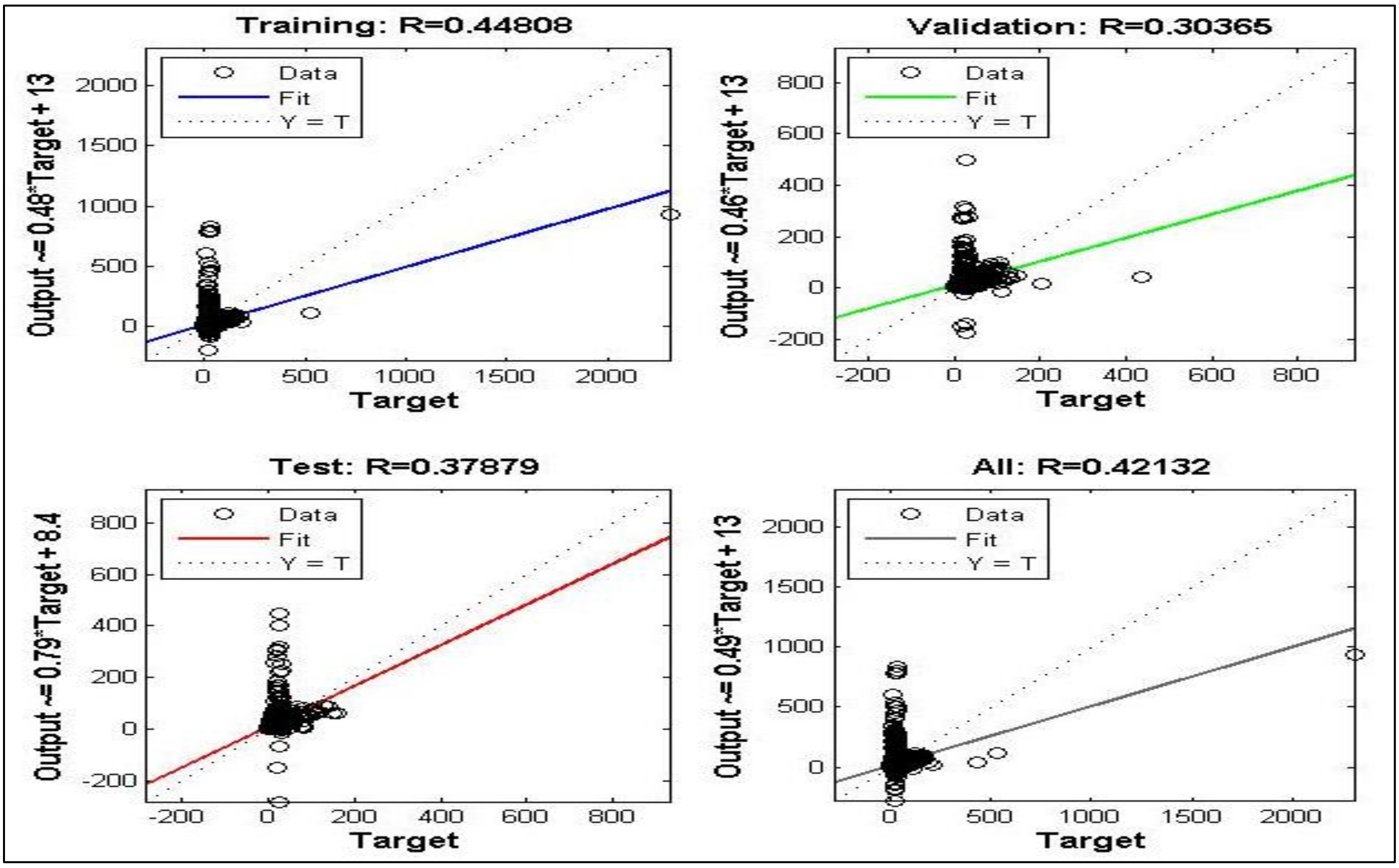


(a)



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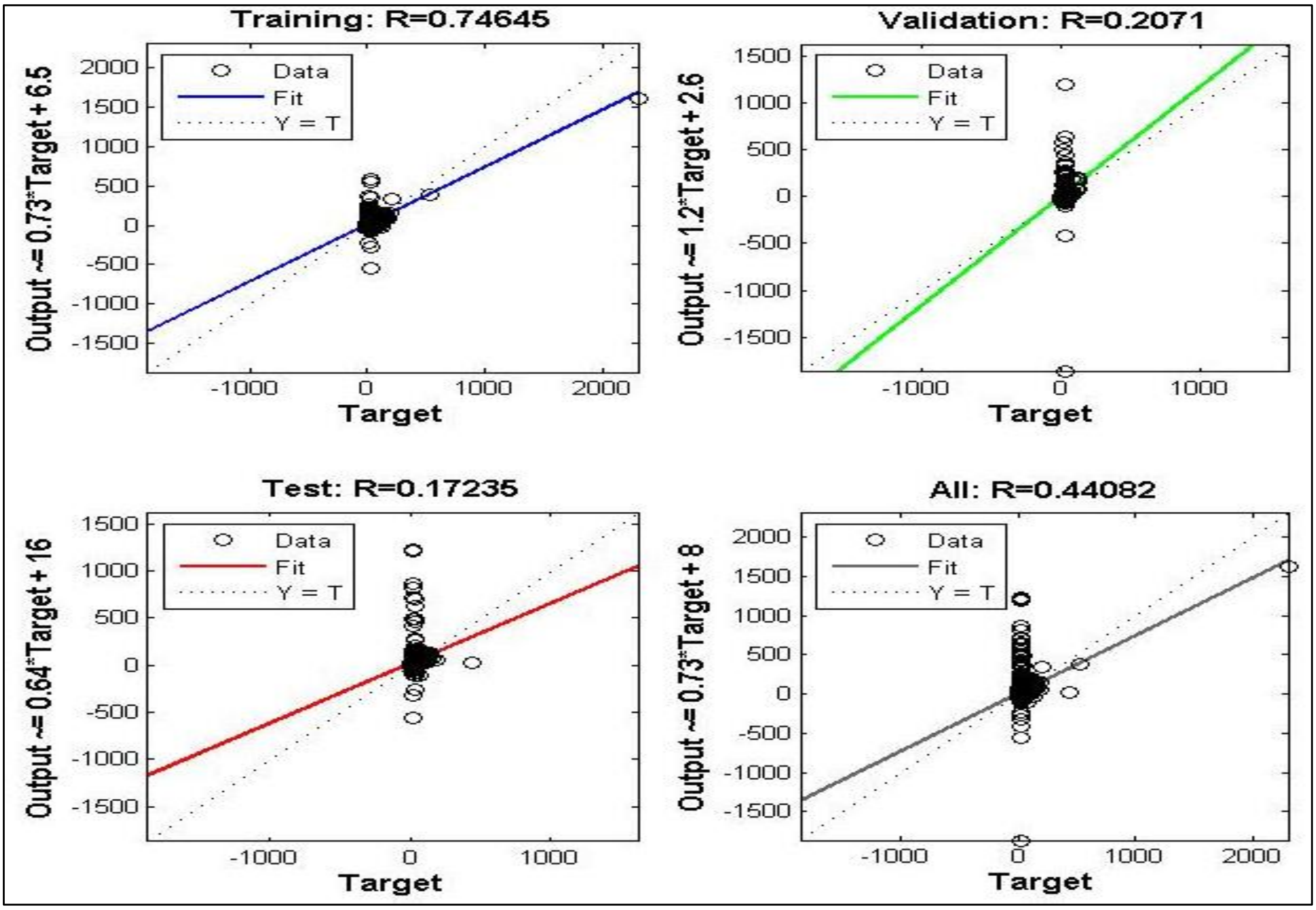
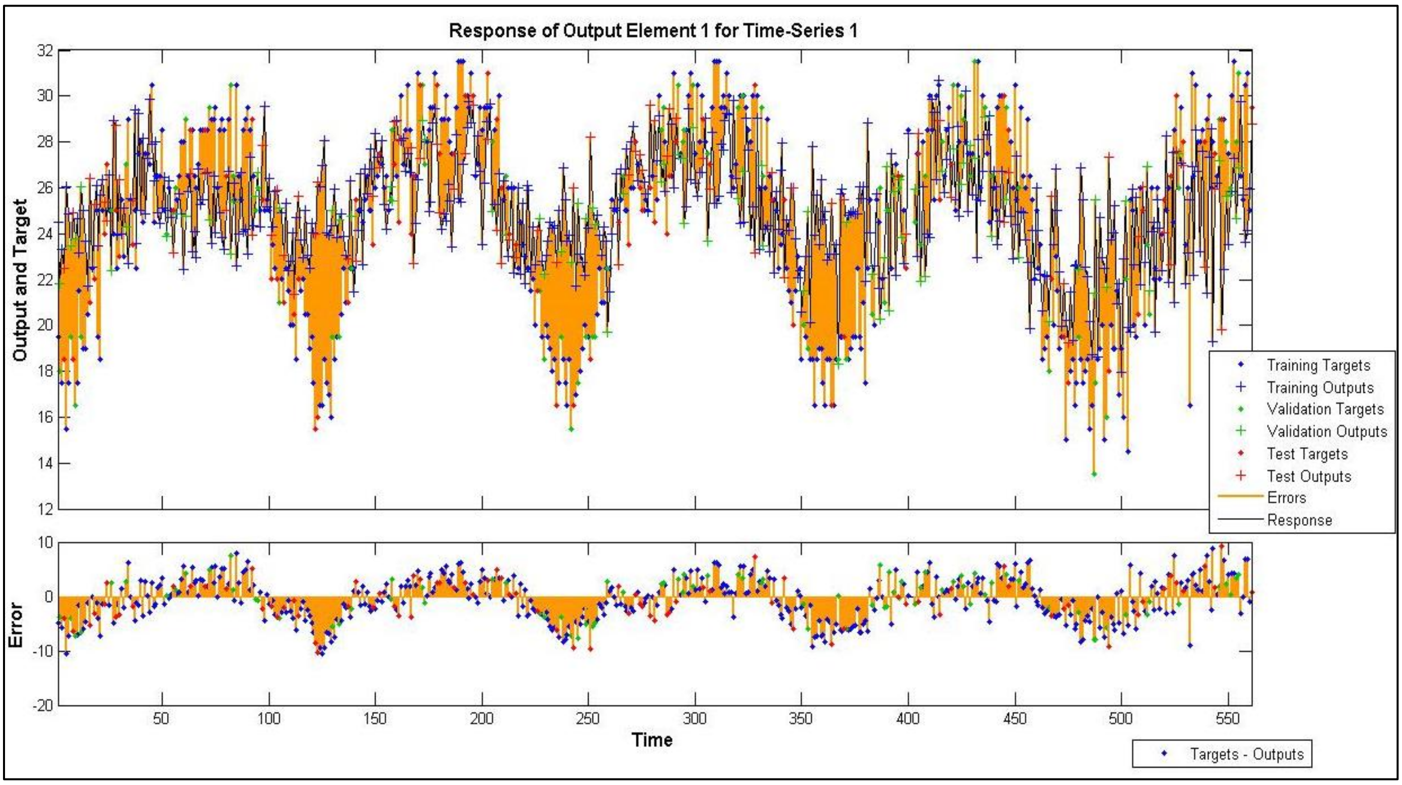


(c)

Fig 3 Comparision of Predicted and Observed PM_{10} Concentrations for First Test Case (a) +3 Days (b) +7 Days and (c) +10 Days



(a)

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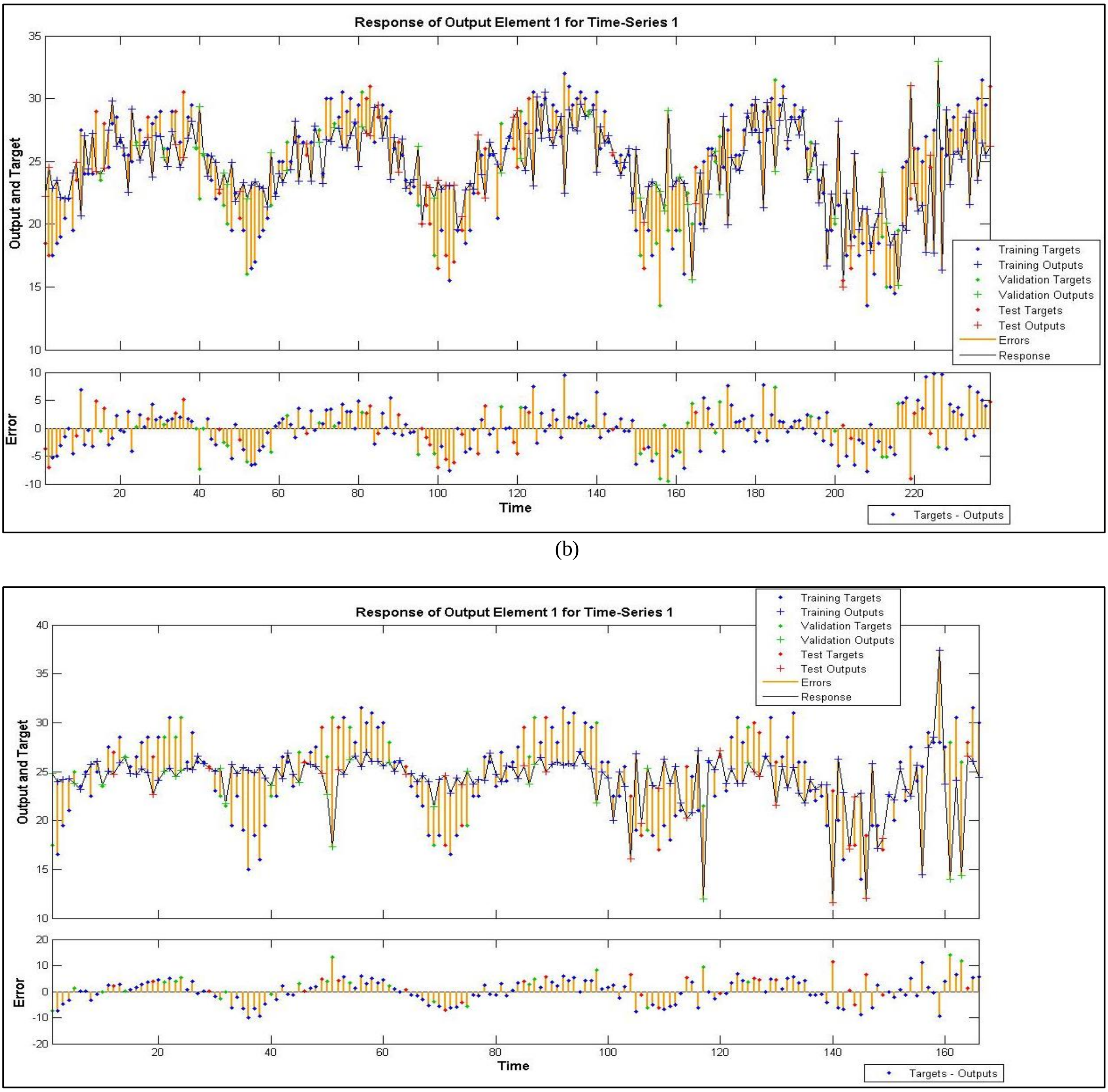

(b)

(c)

Fig 4 Training ANN Model Time Series of the PM_{10} Concentration of the First Test Case for (a) +3 Days (b) +7 Days and (c) +10 Days

As explained in experiment setup section in which +1, +2 and +3 days (PM_{10} concentrations) were predicted cumulatively using previous days' model-predicted values. This is done so as to optimize the number of previous days (PM_{10} concentrations) while training the ANN model to achieve better predictions. In the experimental setup, the forecasting of PM_{10} concentrations for +1, +2, and +3 days is approached in two distinct parts to optimize the training process of the ANN model for enhanced accuracy. In Part 1, separate neural network models are employed to independently predict PM_{10} levels for each of the +1, +2, and +3 days ahead. This method allows each neural network to specialize in predicting PM_{10} concentrations for a specific future time frame. In Part 2, a cumulative modelling strategy is implemented:

- Initially, a model is developed and trained using historical data to predict the PM_{10} concentration for the next day (+1 day).
- The predicted PM_{10} value for +1 day is then incorporated into the training dataset.
- Subsequently, a new model is created using this updated training dataset, which now includes the predicted value

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for +1 day. This new model is used to forecast the PM_{10} concentration for +2 days.

- The forecasted PM_{10} concentration for +2 days is added to the training dataset.
- Finally, another new model is built using this further refined training dataset, which now encompasses predictions for both +1 and +2 days. This model is employed to predict the PM_{10} concentration for +3 days.

This cumulative approach involves iteratively refining the training data to improve the ANN model's ability to predict PM_{10} levels over multiple days. It aims to capture and build upon the relationships and patterns observed in PM_{10} concentrations across consecutive days, potentially enhancing the overall accuracy of the forecasting process. Table 3 shows the comparison of observed and predicted PM_{10} concentrations of Part 1 and Part 2 experimental results in absolute errors (%). It shows that the cumulative method produces better results. The highest gain was observed on +2 day prediction values.

Table 3 Comparison of Independent and Cumulative Predictions (Values in Absolute Error %)

Predicted Day	**PM_{10} (Absolute error in %)**	
	Part 1	**Part 2**
+ 1 day	32	33
+ 2 day	41	41
+ 3 day	47	46

Additionally, another experiment was conducted to determine the optimal size of the training dataset. This experiment compared the performance of different durations, ranging from 3 days to 15 days. It was observed that including more than 15 days did not lead to improved predictive values for the model. Table 4 illustrates the Absolute Errors (AE) of these predictions. Notably, there was a more significant enhancement in predictive accuracy for +1 day compared to +2 day predictions.

Table 4 3 to 15 Days Absolute Errors (%) of the Model Predicted values as Compared to Observed or Measured PM_{10} Concentrations

No. of days	**+1 day**	**+2 day**	**+3 day**
	Absolute errors (%)		
3	33	41	46
4	37	41	46
5	35	43	44
6	35	43	45
7	39	41	42
8	38	39	43
9	37	39	43
10	36	40	44
11	38	40	42
12	37	39	44
13	36	39	43
14	36	39	40
15	37	39	42

The error rates for predicting PM_{10} concentrations for +1, +2, and +3 days were all below 45%, with the most accurate predictions achieved for +1 day. Naturally, higher error rates were observed for +2 and +3 days. Interestingly, the error rate for predicting +1 day PM_{10} concentrations tends to increase slightly as more training data is incorporated, although a less than 35% error rate can be achieved with 3 to 6 days of data. Conversely, the error rates for +2 and +3 days decrease as more training data is used.

According to Gardner and Dorling (1998), PM_{10} exhibits seasonal behaviour, suggesting that the improved performance may be influenced by seasonal effects. Overall, the cumulative method, which optimizes the training dataset, consistently yields higher accuracy than the independent method that uses all past data as the training dataset.

Finally, an experiment was conducted to examine the effect of weekdays on the model's prediction values. Previous studies by Karaca et al. (2005b) and Boznar et al. (1993) have noted variations in air pollution levels depending on factors such as traffic density and operational status of factories on weekends. The daily average PM_{10} concentrations from January 2015 to August 2019 (as shown in Table 5) were utilized as inputs to the ANN model.

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Table 5 Daily Average Air Pollution Concentrations in Imphal from January 2015 to August 2019

Days of Week	**PM_{10} (µg m−3)**
Monday	53
Tuesday	50
Wednesday	52
Thursday	52
Friday	52
Saturday	21
Sunday	47

Table 6 indicates that the average PM_{10} concentration was highest on Thursday and lowest on Sunday. Each day of the week is assigned a number from 1 to 7, representing Sunday to Saturday, and is used as an input parameter in the ANN model. The remaining input parameters in the ANN model remain consistent. Table 6 provides a comparison of the ANN model's predicted and observed values using absolute errors (%), considering whether the day-of-week was included as an input parameter or not.

Table 6 Comparison of ANN Model Performances when Compared with and without Day-of-Week as Model Input

Predicted Day	**PM_{10} (absolute error in %)**	
	Without day-of-week	**With day-of-week**
+ 1 day	33	35
+ 2 day	41	38
+ 3 day	46	42

Including the day-of-week as an input parameter in the ANN model resulted in lower error rates for PM_{10} predictions. Particularly, for +3 day forecasts, the inclusion of the day-of-week parameter led to a 5% reduction in error percentage. This highlights that incorporating the day-of-week enhances the accuracy of forecasting PM_{10} concentrations. Several factors influenced the error rates observed in this study: (i) Meteorological data was sourced from another station in Imphal, potentially impacting prediction accuracy. (ii) Absolute error values were higher compared to relative errors, indicating lower performance, but they are crucial for comparing model optimizations. (iii) Handling missing values, which were replaced with the mean of the nearest existing values, affected the accuracy. The ratio of missing values ranged from 10% to 20%, posing challenges in data integrity and prediction reliability. These factors collectively influenced the outcomes of the study, underscoring the complexities and considerations in improving the predictive capabilities of the ANN model for PM_{10} concentrations.

V. CONCLUSIONS

From the study, the use of PM_{10} data spanning January 2015 to August 2019 (four years and eight months) for developing the ANN model to forecast pollutant concentrations was deemed satisfactory. However, the study suggests that including data on other primary pollutants would have enhanced its comprehensiveness. In Imphal city, while the existing air quality monitoring system meets legal obligations, it falls short of the requirements for effective and high-quality air quality assessment. There is a pressing need to develop a specialized information and telecommunication system capable of continuous data transmission to improve the efficiency of air quality monitoring.

Accurate prediction of hourly PM_{10} concentrations over three, seven, or ten days is crucial for the proposed integrated air quality management scheme. Such data can support real-time decision-making to safeguard public health, particularly for vulnerable groups such as the elderly, children, and individuals with respiratory conditions.

Key outcomes of the study include: (i) Establishment of an air quality prediction system in Imphal. (ii) Provision of effective support for timely actions by relevant authorities. (iii) Issuance of warnings to sensitive groups during periods of hazardous air pollution levels.

The performance of the ANN model can be summarized as follows: (i) Introduction of a cumulative method to improve air pollution predictions for +2 and +3 day forecasts. (ii) Optimization of the number of days used in training to enhance prediction accuracy. (iii) Enhancement of precision by including the day-of-week as an input parameter in the dataset.

Overall, the study underscores the effectiveness of neural network-based models in predicting pollutant levels over short-term periods, laying a foundation for informed air quality management and policy decisions.

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