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Mathematical Modeling For Predicting PM 2.5 And PM 10 Concentrations In Pokhara, Nepal

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Abstract
Particulate matter, specifically PM 2.5 and PM 10 is a threat to the ecosystem; therefore, reducing their concentrations in our surroundings demands motivated steps. The goal of this work is to generate a mathematical formulation that would predict PM 2.5 and PM 10 concentrations in Pokhara. With the meteorological parametric values of Pokhara, the linear regression model (LRM) and the nonlinear regression model (NERM) have been generated. Error evaluation function analysis is applied to the developed models to find out the degree of their variation from the data that has been observed. Error assessment functions ARE, ERRSG, RMSE, MRPE, SEE, and EABS are used. Statistical tools such as R 2, K 2, and F-test are applied to examine the relevance of the generated models. When compared to NERM, the results suggested that LRM has a minor discrepancy from the observed data using the error evaluation function analysis. Additionally, the statistical analysis revealed that LRM correctly matched the observed data better than NERM, and as a result, LRM can be used to analyze the observed data. LRM is a good model for predicting the pollution of the location Pokhara, with reference to graphical comparisons as well. From this study, it is concluded that the LRM is a good choice for predicting the levels of PM 2.5 and PM 10 pollutants in study location.

Keywords: PM 2.5 and PM 10, Regression models, Meteorological parameters, Pokhara.

1. INTRODUCTION

1.1 Background Study

With the increase in air pollution in the recent years, ongoing urbanization and industrialization along with forest fires have created hazardous effects in the daily life of human. Air quality indexes are updated on daily basis in an approach to monitor and alert the citizens.

Air pollution is responsible for one-third of fatalities from stroke, lungs cancer, and many chronic respiratory illnesses, and for one-quarter of fatalities from heart diseases. Air pollutants are also implicated the development of chronic illness or non-communicable diseases (NCD) (Martinez et al., 2018).

Nations with low and middle-income countries are major victims. According to WHO, 99% of people breathe polluted air which is above WHO guideline levels (WHO, 2023). In developing countries like Nepal with population of 29,164,578 population and area of 147,181 sq- km area (National Population and Housing Census, 2021) and HDI of 0.602 (UNDP, September 12, 2022), air pollution is rising as a major health issue. According to national population and housing census 2021, the population of Kathmandu Valley, was 2,041,587 and annual growth was 1.51% with population density of 5169/km ^{2}. In Nepal, the population is trending toward greater urbanization. (National Population and Housing Census, 2021). Majority of urban centers of Nepal are linked to unfavorable meteorological conditions with topographic features such as plain areas, deep valleys and narrow river basins, allowing poor carrying capacity for air and potential to produce severe levels of air pollution even in areas where local emissions are low (Regmi,2013).

Particulate matter (noted by PM) is composed of solid particles with liquid droplets in air. Particulate matter of PM $_{10}$ $(\leq 10\mu m)$, PM $_{2.5}$ $(\leq 2\mu m)$ which are fine unlike large particulate the smoke, soot, dust, dirt which are visible by naked eyes. Particles are released as byproducts of power plants, vehicles and industries. Particles of diameter especially those of size 2.5 μm and lesser are so small that they can enter the respiratory system and reach the alveoli of lungs wherein they cause hazardous effect to lungs and on entering bloodstream circulation (EPA, United State Environmental Protection Agency, 2023).

Particulate matter concentrations frequently surpass critical thresholds that have detrimentally affected the people in Kathmandu, Nepal. Kathmandu being in valley topography where meteorological parameters have major role, it further adds up to the issue (Giri et al., 2008).

Four-variable multiple linear regression models (LRM) and four-variable non- linear exponential regression model (NLERM) are given respectively as follows:

$z = b_0 + by_1 + b_2y_2 + b_3y_3 + b_4y_4 + \varepsilon$, and

$z = \exp\,(c_0 + c_1y_1 + c_2y_2 + c_3y_3 + c_4y_4 + \varepsilon)$.

The coefficients in the above equations are obtained using matrix approach or any other suitable statistical software with help of meteorological parametric values (Alvin and Bruce, 2008).

Nepal is in a serious threat to this detrimental effect of air pollution. Models and researchers have been carried out at international level to predict the particulate matter concentration using meteorological parameters and others but at national level (In Nepal), no research has been carried out on PM prediction using LRM and NERM. There isn't any research on PM prediction in the Nepali contest using LRM and NERM. Therefore, the purpose of this research is to study the particulate matter and forecast PM $_{2.5}$ and PM $_{10}$ role in monitoring air pollution.

1.2 REVIEW OF LITERATURE

Alpan and Sekeroglu have applied three basic machine learning algorithms: support vector regression, random forest, and decision tree and predicted the concentrations of 6 impurities in air, ie, Particulate matter PM $_{2.5,}$ Ozone, Carbon monoxide, Sulfur dioxide, Particulate matter PM $_{10}$, and Nitrogen dioxide. The algorithms took into account only meteorological data. According to experiments conducted on two distinct datasets, only meteorological data, high-accuracy predictions (R2:0.74-0.86) on pollutant concentrations can be made using the random forest, (Alpan and Sekeroglu, 2020).

In two South Korean cities, LSTM network was used by Qadeer et al., 2020 to forecast PM $_{2.5}$ concentration in next hours using previous 24 hours' worth of data from 16 forecasters.

In 2020, Su et al. presented a technique for forecasting ozone O_3 concentration depending on support vector machine regression (i.e., SVR) and kernel extreme learning (i.e., KELM) machine. In summers of 2014-2016, hourly O_3 concentrations and meteorological information (data) was used and suggested model was assessed using a number of measures, including co-efficient of determination (i.e., R^2) and root mean squared error (i.e., RMSE). They concluded that the suggested approach performed better in comparison than linear regression and back propagation neural network models.

Using mathematical models of (linear and logarithmic) multiple regression, artificial neural networks (i.e., ANN) and RF, Sudipta Roy, et al used R statistical packages to forecast concentration of PM $_{2.5}$ as a function of PM_{10}. Mean ratios of PM $_{2.5}$ to PM $_{10}$ gathered from 11 Air Monitoring Stations (known as CAMS) in few major Bangladesh cities were found to be marginally higher during dry seasons in comparison with wet seasons. Although all models are statistically effective, ANN model outperformed (Sudipta Roy, et al, 2022).

Samir et al. investigated the effects of temperature, air pressure, humidity and wind spread on PM_{10} pollutant concentrations (Samir et al., 2016).

Relative humidity had a positive association whereas temperature had an inverse relationship with PM $_{10}$ according to study by Garman et al. 2017.

The analysis by Yansui et al. on pollutants air and climate in china demonstrated significant positive relationship within air pollution concentrations and air pressure but a substantial negative correlation with speed of wind, precipitation, and humidity (Yansui et al., 2020). Non-linear models (although not specified) was found more accurate than linear models (Licheng et al., 2021).

NERM is the most suitable among the models (Salami, L., 2022) in a study in city of Sarajevo. Mikalai et al. have looked at the hourly mass concentrations for PM $_{2.5}$ and PM $_{10}$ that were collected in Gansu Province's 11 largest cities between June 1 and August 31, 2015. In every city that was examined, there were no discernible change between weekday and weekend particulate matter concentrations and other air contaminants (SO_2, NO_2, CO, and O_3) (Mikalai et al., 2016).

Gupta et al. applied various methods to estimate PM $_{10}$ and PM $_{2.5}$ (Particulate matters that are less than 10 and 2.5 micrometers aerodynamic diameters) in 11 cities of Bangladesh. Their study demonstrated the panic state of particulate matters pollution in Bangladesh cities and suggested a simple plan for routine particulate matters monitoring that will support in the fight against pollution (Gupta et al., 2020).

PM $_{2.5}$ concentrations in urban residential buildings' rooms were provided in the paper Liu et al.. In this paper, they compiled the measured concentrations of PM $_{2.5}$ indoors from studies that measured the concentrations in various parts of the world. The factors responsible for variations in indoor concentrations were determined and elucidated (Liu et al., 2022).

The study (Nebras et al., 2020) put forth a comparative analysis to determine the effects of pollutants, such as PM levels, on human in Oman and the Arab world in general. In addition, the study proposed three mathematical models that provide a quick, affordable, and secure way to forecast pollution levels in the future. The first mathematical formulation is the linear regression prediction model that is affordable, simple to use, and produces good results. Nevertheless, the R^2, MSE, and RMSE results of the linear regression models are lower (0.7604, 0.0673, and 0.2595, respectively). When compared to laboratory data, another mathematical model: A non-linear regression polynomial prediction formulation predicted pollution data with remarkable accuracy (Nebras et al., 2020).

The relationships in meteorological phenomena and air pollution in Kathmandu Valley's bottom atmosphere are the subject of the study by Giri et al. The study determined the relationship between the elemental PM $_{10}$ concentrations in the Kathmandu Valley and meteorological components like temperature, precipitation, humidity, atmospheric pressure, wind direction, and speed. The average PM_{10} concentration in the Kathmandu Valley was negatively correlated with increases in humidity and rainfall. According to Giri et al., 2008, the work also suggests that wind velocity and atmospheric pressure cause an increase in the mean PM $_{10}$ in the Kathmandu Valley.

The ambient PM concentrations (PM $_{10}$) at a system of 6 air monitoring places in the capital of Nepal, Kathmandu from 2003 to 2005 were analyzed and interpreted in the paper given by Giri et al.,2006. According to the study, roadside area-representative air sampling sites consistently have higher particulate matter concentrations (PM $_{10}$) than background sites (Giri et al., 2006).

Concerns about pollution in Nepal and other nations have been voiced frequently. There are a lot of studies that discuss how to estimate particulate matter concentrations using meteorological factors and various models. There isn't any research on PM prediction in the Nepali contest utilizing LRM and NLERM. Therefore, the purpose of this research is to forecast particulate matter ($PM_{2.5}$ and PM_{10}) at an air pollution monitoring place in Nepal.

2. METHODOLOGY

2.1 Sources and Type of Data

For the study, the secondary PM $_{10}$ and PM $_{2.5}$ data for eight months February to September, 2021 were extracted from Government of Nepal, Ministry of Forest and Environment Ministry, Department of

Environment, Air Quality Monitoring Stations, https://pollution.gov.np, https:/www.doenv.gov.np/np. Department of Hydrology and Meteorology, Government of Nepal, https://www.dhm.gov.np.
The secondary PM $_{10}$ and PM $_{2.5}$ data have taken in terms of time period. Set of monthly data series are arranged in chronological method. The monthly average secondary PM $_{10}$ and PM $_{2.5}$ data and meteorological parametric values which are used for the study are listed in the following tables (Climate and Pollution data, 2021).

Table 1. Monthly average $PM_{2.5}$ with Pokhara parameters

Months	Temp.(°F)	Humidity (%)	W. Speed (m/s)	Pressure	$PM_{2.5}$ (ug/m^3)
Feb.	66	64	3.8	26.9	46.79
March	72	61	3.8	26.9	83.16
April	77	50	4.0	26.9	85.33
May	75	79	3.8	26.8	16.31
June	79	86	3.6	26.7	12.83
July	82	88	3.4	26.7	7.76
August	81	90	3.4	26.8	7.57
September	79	84	3.6	26.9	8.45

Table 2. Monthly average PM_{10} with Pokhara parameters

Months	Temp.(°F)	Humidity (%)	W. Speed (m/s)	Pressure	PM_{10} (ug/m^3)
Feb.	66	64	3.8	26.9	61.34
March	72	61	3.8	26.9	82.61
April	77	50	4.0	26.9	86.63
May	75	79	3.8	26.8	22.26
June	79	86	3.6	26.7	18.31
July	82	88	3.4	26.7	9.97
August	81	90	3.4	26.8	8.77
September	79	84	3.6	26.9	10.86

In this research, the secondary PM $_{10}$ and PM $_{2.5}$ data have collected from the authorized offices air quality monitoring center and source of Pokhara of Nepal. The formulations of the mathematical framework for predicting the concentrations of the particulate matters of the city have derived with help of Linear Regression Model (LRM) and Non- Linear Exponential Regression Model (NERM).
To find out how the models differed from the original data, error evaluation functions analysis have also used to the final models. Some of the error evaluation functions are: Root Means Square Error (RMSE), Marquardt's Percent Standard Deviation (MPSD), Average Relative Error (ARE), and Sum of Error Square (ERRSQ).
The predicted concentrations from the two obtained models have compared with the real PM $_{10}$ and PM $_{2.5}$ data.

The four-variable multiple linear regression models (LRM) is applied as:

$$z = b_0 + by_1 + b_2y_2 + b_3y_3 + b_4y_4 + \varepsilon,, \quad (1)$$

and the four-variable non- linear exponential regression model (NLERM) is applied as:

$$z = \exp\,(c_0 + c_1y_1 + c_2y_2 + c_3y_3 + c_4y_4 + \varepsilon). \quad (2)$$

Here, y represents the particulate matters for Pokhara and the coefficients are obtained using meteorological parametric values (Alvin and Bruce, 2008).

To verify how much the predicted data matches the observed data , error evaluation function analysis model, which are shown in equations 3- 11, have been applied to the observed and predicted data .

$$(ARE) = \frac{1}{N}\sqrt{\sum_{k=1}^{N}\left(\frac{z_o - z_p}{z_o}\right)^2} \quad (3)$$

where z_o= observed data

z_p= predicted data

N= number of experimental data

$$ERRSQ = \frac{1}{N}\sum_{k=1}^{N}(z_o - z_p)^2 \quad (4)$$

$$MPSD = \sqrt{\frac{1}{N-N_p}\sum_{k=1}^{N}\left(\frac{z_o - z_p}{z_p}\right)^2} \quad (5)$$

where N_p= No. of parameter(s)

$$HYBRID = \frac{1}{N-N_p}\sum_{k=1}^{N}\left[\frac{(z_o - z_p)^2}{z_o}\right] \quad (6)$$

$$RMSE = \frac{1}{N-2}\sqrt{\sum_{k=1}^{N}(z_o - z_p)^2} \quad (7)$$

$$EABS = \sum_{k=1}^{N}(z_o - z_p)^2 \quad (8)$$

$$x^2 = \sum_{k=1}^{N}\left[\frac{(z_o - z_p)^2}{z_p}\right] \quad (9)$$

$$SEE = \sqrt{\frac{\sum_{k=1}^{N}(z_o - z_p)^2}{N-2}} \quad (10)$$

$$MRPE = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{z_o - z_p}{z_o}\right) \quad (11)$$

2.2 Statistical Analysis

To find a good model that almost represents the observed data to a high degree, statistical tools such as the models from 12-16 are applied, which helped to select the good models within the developed models.

$$r = \frac{\sum_{k=1}^{N}(z_o - z_o^{-})(z_p - z_p^{-})}{\sqrt{\sum_{k=1}^{N}(z_o - z_o^{-})^2 \sum_{k=1}^{N}(z_p - z_p^{-})^2}} \tag{12}$$

where z_o^{-} = mean value of observed data

z_p^{-}= mean value of predicted data

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(z_o - z_p)^2}{\sum_{k=1}^{N}(z_o - z_o^{-})^2} \tag{13}$$

$$K^2 = \frac{\sum_{k=1}^{N}(z_o - z_p)^2}{\sum_{k=1}^{N}(z_o - z_o^{-})^2} \tag{14}$$

$$t - test = \frac{(\overline{z_o} - z_p^{-})}{\sqrt{s^2\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}} \tag{15}$$

here s^2= standard error

N_1 and N_2 are the observed and developed data from model respectively.

here, we take, $N_1=N_2=N$

$$F - test = \frac{\frac{\sum_{k=1}^{N}(z_o - z_o^{-})^2}{N-1}}{\frac{\sum_{k=1}^{N}(z_p - z_p^{-})^2}{N-1}} \tag{16}$$

Matlab (Matrix Laboratory) is a proprietary numerical computing environment and multi-paradigm programming language was created by Math Works. Matlab enables matrix manipulation, user interface design and connectivity with other programming languages (Wikipedia.org). In this work, graphs and tables are drawn using MATLAB R2015a to determine the trend of the particulate matters in Pokhara, Nepal and to compare and contrast the graphs from the data and models.

3. RESULTS, ANALYSIS AND DISCUSSION

The LRM and NERM models for different pollutants are developed with the help of used parameters which are given by equations (17) to (20) respectively. Generated models have been applied to compare the observed data. Observed and predicted data for the generated model for Pokhara are given in Table 1and 2.

LRM and NERM models for Pokhara $PM_{2.5}$ are:

$$z = 1502.91 - 33.65y_1 - 65.21y_2 - 2.89y_3 - 1.41y_4 \tag{17}$$

and $z = \exp(77.83402 - 2.31743y_1 - 0.56933y_2 - 0.07181y_3 - 0.06711y_4)$ (18)

LRM and NERM models for Pokhara PM_{10} are:

$$z = 1676.04 - 42.79y_1 - 47.94y_2 - 2.58y_3 - 1.58y_4 \tag{19}$$

and $z = \exp(72.03142 - 2.28551y_1 - 0.311706y_2 - 0.05293y_3 - 0.06098y_4)$ (20)

Table 3. Observed and predicted $PM_{2.5}$ for Pokhara

Months	z_o	LRM z_p	NERM z_p
Feb	46.79	62.85029	49.6007
March	83.16	80.01398	90.0171
April	85.33	83.27151	90.01713
May	16.31	18.55157	17.2877
June	12.83	9.042084	11.3785
July	7.76	12.0554	9.025
August	7.57	4.313452	6.6352
September	8.45	8.101708	8.2631

Table 4. Observed and predicted PM_{10} for Pokhara

Months	z_o	LRM z_p	NERM z_p
Feb.	61.34	63.92262	52.4573
March	82.61	81.13651	88.23
April.	86.63	82.5106	86.1422
May	22.26	24.80552	24.7543
June	18.31	14.31205	14.87
July	9.97	14.00452	11.023
August	8.77	6.151333	8.469
September	10.86	10.90684	11.0231

The graphical study of pollutants from observed, predicted (LRM), and predicted (NERM) data is given below:

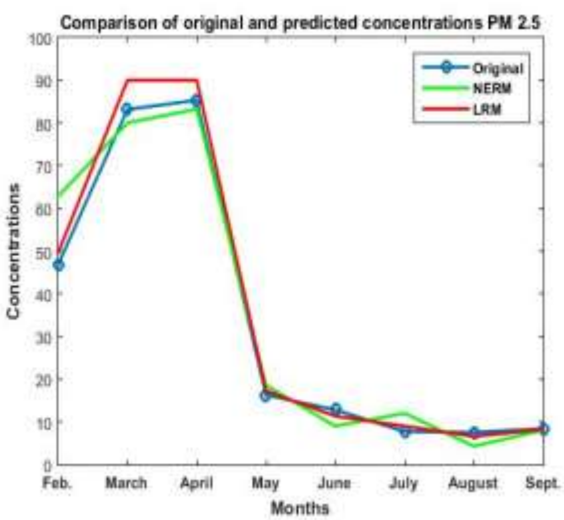


Figure 1. Monthly Data Comparison, Pokhara $PM_{2.5}$

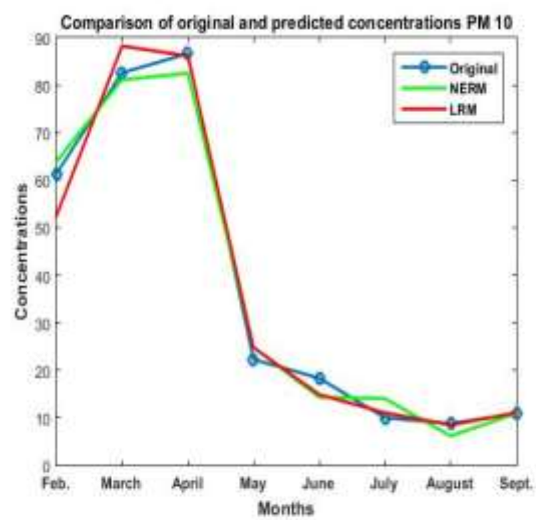
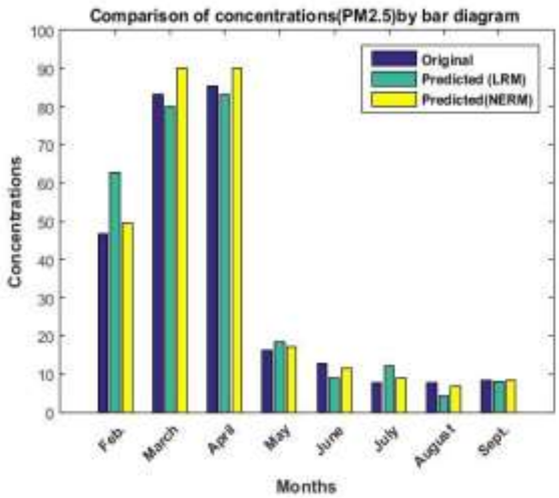


Figure 2. Monthly Data Comparison, Pokhara PM_{10}



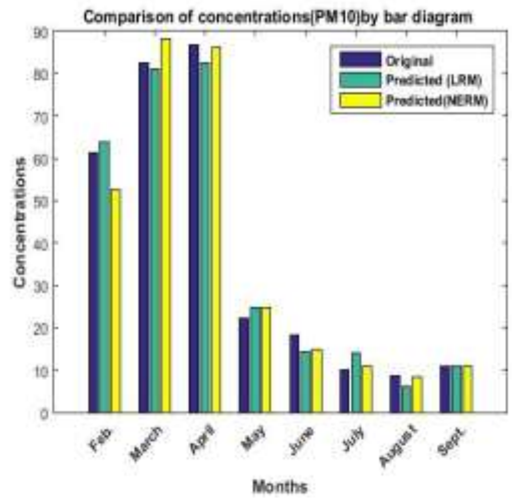


Figure 3. Monthly Data Comparison, Pokhara $PM_{2.5}$ **Figure 4.** Monthly Data Comparison, Pokhara PM_{10}

We have found that, both graphically and diagrammatically, the predicted pollutants provided by the model LRM more closely matched the original contaminants than the predicted pollutants provided by the NERM. Thus, we choose the LRM model over the NERM model for the prediction of pollutants in Pokhara.
The model that best fits the observed data was chosen from among the produced models using the study of error evaluation functions. To choose the model that more accurately matches the observed data; statistical tools have also been applied to examine the observed and predicted data in order to determine how applicable the developed models are. Table 4 lists the statistical tools that are used as the evaluation formulas in this research. ARE results for NERM and LRM in Table are 0.0978208343 and 0.2907696683, respectively. The goodness of fit between the anticipated and observed data is evaluated using ARE. It reduces the fractional error distribution throughout the whole inclusive data range (Rahman et al.2008). The better the forecast, the lower ARE value. LRM has the lowest ARE, indicating that it predicts the observed data correctly.
A tool called ERRSQ is used in regression analysis to determine the dispersion of data and the degree to which a given set of data would fit a model. It is a frequently used error evaluation function. In this study, the ERRSG readings for NERM and LRM are 15.70466 and 12.90676, respectively. The model's ability to predict the observed data improves with a lower ERRSQ value. This showed that, because of its small ERRSQ value, LRM correctly predicted the observed data.
The variation between observed and obtained data from predicted model is measured by SEE. It is crucial for verifying the prediction's accuracy. Between the two generated models, LRM matched the observed data more accurately, with SEE values for LRM and NERM being 4.0704422364 and 4.587061514, respectively.

Table 5. Results of Error evaluation functions for Pokhara $PM_{2.5}$

S.N.	Error Function Model	LRM	NERM
1	ARE	0.0978208343	0.2907996683
2	ERRSQ	12.42637	15.78085
3	MPSD	0.1956416686	0.072692417
4	RMSE	1.6617510845	1.872660021
5	EABS	99.411	126.2468
6	SEE	4.0704422364	4.587061514
7	MRPE	0.0038652695	0.01057125

Table 6. Results of Statistical evaluation for Pokhara $PM_{2.5}$

S.N.	Parameters	LRM	NERM
1	r	0.9940415602	0.9944610318
2	R^2	0.988118743	0.9849114197
3	K^2	0.011881257	0.0150885803
5	F- test	1.012024241	0.8965822785

Table 7. Results of Error evaluation functions for Pokhara PM_{10}

S.N.	Error Evaluation Function	LRM	NERM
1	ARE	0.076577	0.1031635226
2	ERRSQ	12.42648125	17.0098275
3	MPSD	0.4744307115	0.1308768505
4	RMSE	1.6617581887	1.9442157807
5	EABS	99.41185	136.0791
6	SEE	4.0704596383	4.7623366114
7	MRPE	0.00386525	0.2065485

Table 8. Results of Statistical evaluation for Pokhara PM_{10}

S.N.	Parameters	LRM	NERM
1	r	0.9123813192	0.9917615385
2	R^2	0.9881186414	0.9821514984
3	K^2	0.0118813586	0.0178485016
5	F- test	1.002210073	0.9433928575

The degree of linearity is shown by the values, which range from -1 to +1. A high degree of negative and positive relationships between the observed and developed results can be determined by values of r that are close to -1 and +1.

The percentage of the expected data differences that can be estimated based on the observed data is known as R^2.

In the evaluation of regression analysis, R^2 supplied more details than ERRSQ, MPSD, RMSE, and SEE as it is capable of being stated in percent form, whereas the other measurements have random ranges. A strong R^2 value suggests the model fits the data well.

The best model out of the constructed models is the LRM, which has a high R^2 value and can predict 98.81 percent of the observed data. As a result, the LRM is a suitable model to select for predicting the concentrations of PM pollutants in Pokhara City.

The difference between observed and predicted data that is not entirely explained or compensated for is termed K^2. The model will perform better with a lower K^2 value. Less than 9% of the observed data are not explained by the LRM, corresponding to the LRM's small K^2 value between the developed models. This showed that, in comparison to NERM, LRM accurately represented the observed data.

For LRM and NERM, the F-test results have been found to be 1.012024241 and 0.8965822785, respectively. Given that, the generated model as a whole completed the F-test, the observed data will be represented by the model having the smallest F-test value. As a result, LRM has been accepted as more effective than NERM.

It is clear that, when compared to NERM, LRM shows the minimum variation from the observed data according to the study of error evaluating functions conducted in this study to determine the error variation of the obtained models. The LRM mathematical model has been applied to estimate the PM pollutants in Pokhara City.

The LRM model has been selected for the estimation of levels of PM in Pokhara as it more accurately matched the observed data than the NERM, as demonstrated by the statistical evaluating tools applied to find the relevance of the generated models.
From error evaluation functions, statistical analysis, and graphical comparison of observed and predicted data from both mathematical models of Pokhara, it is found that LRM is a better model than NERM for PM_{10} as well. In all the cases, LRM has shown the minimum variation from the observed data according to the study of error evaluation functions, statistical analysis, and graphs constructed in this research.

4. SUMMARY AND CONCLUSION

A mathematical model has been established to predict the level of PM pollution in Pokhara City. To find out how far the generated models deviate from the observed data, LRM and NERM established and examined error evaluation functions. Statistical tools have also been used to examine the practicality of the proposed models. When compared to NERM, the LRM exhibited a small degree of deviation from the observed data. Additionally, LRM has been used for the exploration of the observed data produced for PM pollution levels in Pokhara because it predicts the observed data more precisely than NERM in terms of statistical analysis. It has been determined that the concentrations of PM pollutants in the Pokhara can be predicted using the LRM model.
Using error evaluation functions and statistical analysis with graphs, it is also concluded that LRM is a more reliable predicted model than NERM for PM_{10} of Pokhara. Based on the statistical examination, error evaluation functions, and graphs constructed for this research, LRM regularly showed a small amount of deviation from the observed data.

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