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Effects of Traffic on Particulate Matter ($PM_{2.5}$) in Different Built Environments

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ABSTRACT

Globally, vehicular pollution is one of the greatest concerns in urban areas. Several studies on air pollution have been conducted using deterministic, statistical, and soft computing methods. However, there has been little research on how soft-computing methods like Artificial Neural Networks (ANN) can help us comprehend vehicular pollution's non-linear and highly complex dispersion. This study uses an ANN-based vehicular pollution model to investigate the effect of vehicular traffic on $PM_{2.5}$ concentrations in built-up and open terrain-surrounding environments. Five distinct pollution models were developed for two locations in Delhi, considering $PM_{2.5}$ pollutants, meteorological variables, traffic flow, and traffic composition into account. The results concluded that under open terrain conditions, the significance of the traffic variable in its association with $PM_{2.5}$ is almost half the significance observed under built-up conditions. Also, in terms of $PM_{2.5}$ reductions, the maximum reduction observed at Location-1 (built-up environment), and Location-2 (open terrain environment) is 1.85 and 2.44 times the percent reduction in traffic during peak hours, respectively. The study's findings have significant ramifications for the current practices of ignoring the contribution of traffic and the built environment to pollution and adopting measures like an odd-even rule and high fuel and parking prices to combat pollution.

INTRODUCTION

The World Health Organization (WHO 1980) defines air pollution as "contamination of the indoor or outdoor environment by any chemical, physical, or biological agent that modifies the natural characteristics of the atmosphere." India is the fifth country in the world in terms of worst air quality and the fourth-largest emitter of greenhouse gases (UNEP 2019). A recent study analyzed pollution and global health effects for more than 7,000 cities worldwide between 2010 and 2019 (Health Effects Institute 2022). Delhi ranked first in the list of the top 10 most polluted cities when $PM_{2.5}$ levels were compared.

According to a recent study (Health Effects Institute 2022) that analyzed pollution and global health effects for over 7,000 cities worldwide between 2010 and 2019, Delhi ranked first among the top 10 most polluted cities in terms of $PM_{2.5}$ contributions. In 2019, Delhi's average annual $PM_{2.5}$ concentration was 110 $\mu g.m^{-3}$, nearly three times the regulatory threshold of 40 $\mu g.m^{-3}$.

Several pollution studies have been conducted over the past two decades; however, developing a reliable vehicular pollution model is still a challenge due to a large number of dynamic and influencing variables (such as wind speed, direction, vehicle wake, etc.) that have a significant impact on the pollution. This demonstrates the clear need for a better understanding of the sources and dispersion of pollution or a reliable model for pollution prediction. This paper discusses the results of an ANN-based vehicular pollution model and the contribution of traffic to $PM_{2.5}$ under two distinct boundary conditions.

OVERVIEW OF VEHICULAR POLLUTION MODELLING

Modeling approaches for vehicular pollution modeling are broadly categorized as a deterministic, statistical, hybrid of statistical and deterministic approaches, and soft-computing (Nagendra & Khare 2004). Deterministic models estimate pollutant concentration from datasets related to emission inventory and meteorological variables, whereas statistical/empirical models predict pollutant concentration by establishing statistical relationships between the dependent (pollutant concentrations) and independent variables (meteorological, traffic). Several researchers have concluded that deterministic models are relatively accurate at predicting air pollution and valuable for long-term planning choices. However, they do not adequately model vehicular pollution (Khare & Nagendra 2007). The accuracy of deterministic models is contingent on whether their underlying assumptions are satisfied. Similarly, statistical

Table 1: Review of Indian case studies related to pollution modeling.

Reference	Approach	Variables
(Gupta et al. 2023)	CALINE	1,2,3,5
(Dass et al. 2021)	Fuzzy	1, 2
(Dutta & Jinsart 2021)	Comparison of Multi Linear Regression (MLR) and ANN	1,2
(Kaur & Mandal 2020)	ANN	1,2
(Agarwal et al. 2020)	ANN	1,2
(Yadav & Nath 2018)	Comparison of Principal Component Analysis, MLR, and ANN)	1,2
(Dhyani et al. 2017)	CALINE-based Gaussian plume dispersion model	1,2,3
(Mishra et al. 2015)	Comparison of MLR, Neuro-Fuzzy, and ANN	1,2
(Kumar et al. 2015)	CALINE	1,2,4,5,6
(Singh et al. 2013)	Statistical (Decision Tree)	1,2
(Prakash et al. 2011)	Soft Computing (Recurrent Neural Network)	1,2

Note: 1- Pollutant; 2- Meteorological; 3- Traffic and road characteristics; 4- Land use; 5- Surface characteristics; 6- Source emission data

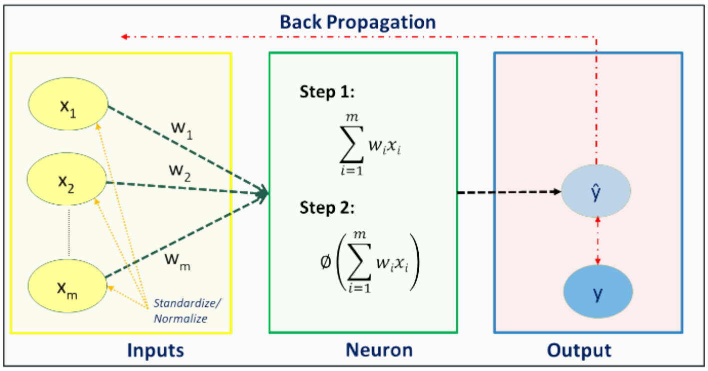

Fig. 1: ANN architecture.

models yield superior results for site-specific analyses but subpar results for nonlinear data sets.

In the recent past, numerous modeling studies have been conducted using multi-layer neural networks to forecast PM, NO_2, O_3, and SO_2 concentrations, whereas the application of neural networks to model vehicular pollution is limited (Batterman et al. 2014, Heydari et al. 2021, Kumar 2016, Rahimi 2017, Shams et al. 2021, Sofuoglu et al. 2006).

Table 1 above summarizes several Indian case studies relating to air pollution/vehicle pollution modeling over the years. Considering the non-linear and complex relationships in the environment, these research papers suggest neural networks and other soft computing techniques for modeling air pollution. In terms of vehicular pollution modeling, however, deterministic or statistical approaches predominate. In addition, the results predicted by deterministic models are more reliable than those predicted by statistical approaches if the plume model's boundary conditions are precisely defined.

VEHICULAR POLLUTION MODELLING USING ANN

ANN is an offshoot of artificial intelligence developed in the 1950s to mimic the architecture of the biological brain. It has since become an indispensable tool for modeling nonlinear dynamic processes. The neural network approach is a promising alternative to conventional models due to its self-correcting, self-learning, and similar processing characteristics (Khare & Nagendra 2007). The fundamental architecture of ANN is depicted in Fig. 1.

It consists of input layers, hidden layers, and output layers. The number of input layers matches the number of independent variables. Hyper-parameters refer to the number of neurons in the hidden layers, the number of layers, and various other neural network parameters, such as the learning rate, activation function, learning algorithm, number of epochs, batch size, etc. These hyper-parameters are optimized to improve the model's performance.

In ANN, the multi-layer neural network has been widely used in air pollution research due to its ability to model highly nonlinear relationships and generalize accurately when treated with new, unseen data (Abiodun et al. 2018, Gardner & Dorling 1998). To obtain good model results, it is essential to avoid overtraining neural networks, in which the model learns insignificant details in the training data, resulting in poor generalization when tested with new, unseen data (Bilbao & Bilbao 2017).

To avoid overtraining neural networks, models are typically trained on a subset of inputs and outputs to determine weights and then validated on the remaining data to determine the accuracy of model predictions. The dataset is separated into training, test, and validation datasets. The training dataset is used to evaluate the model's generalization performance during training. Training is complete when the model's performance on the test dataset reaches its maximum. The test dataset is not utilized during the modeling process but at the conclusion to evaluate the model's predictability beyond the training dataset. The final neural network model and hyper-parameter tuning are evaluated by utilizing the validation dataset.

The following six sequential steps have been followed to model vehicular pollution using ANN:

1. Selecting Optimal ANN-based Vehicular Pollution Model Architecture
2. Selecting the Best Activation/Transfer Function
3. Selecting Optimum Learning Parameters
4. Initializing Network Weights and Bias
5. Model Training and Generalization
6. Model Evaluation

INTRODUCTION TO SURVEY LOCATIONS

In this study, a vehicular pollution model was developed for two locations, Location-1: Bahadur Shah Zafar Road (28.63°, 77.24°), one of the busiest corridors in Delhi, the National Capital of India, and Location-2: Near Millenium Depot (28.59°, 77.26°). The right of way for Location-1 is 40 m, and for Location-2 is 70 m. The locations have a kerbside air quality sampling station (approximately 3 meters above the ground) monitored by the Central Pollution Control Board (CPCB). The source apportionment study (CPCB 2016) for Delhi also revealed that nearly 30 percent of the observed pollution at Location-1 is caused by vehicular traffic. The predominant land uses surrounding Location-1 are commercial and institutional, and predominantly urban green and blue spaces surrounding Location-2.

MATERIALS AND METHODS

Pollutant Data

The CPCB provided the hourly pollutant data set ($PM_{2.5}$ concentrations, $g.m^{-3}$) for January 2019 that was used for training, validating, and testing the predictive ability of the ANN model at both locations.

Meteorological Data

The hourly meteorological data set for January 2019 was collected for the closest weather station at Safdarjung (approximately 10 km from these locations). The input variables in the study are temperature in °C, dew point temperature in °C, relative humidity in %, precipitation in mm, wind direction in degrees, wind speed in $Km.h^{-1}$, mixing height in meters, and atmospheric pressure in hPa.

Traffic Data

Using videography surveys, 16 hours of traffic data were collected on one weekday (Monday) and one weekend day (Sunday) in January 2019 for both locations. The data have been extrapolated to a 24 h count, and an adjustment factor for daily variation has been assumed based on fuel sales data from the station closest to the sites (less than 1 km). The average daily volume at Location-1 is 1,45,356 Passenger Car Units (PCU). Peak-hour traffic is observed between 10:30 and 11:30 a.m. The percentage composition of weekday and weekend traffic is nearly identical, with two- and four-wheeler vehicles accounting for 77 percent of the total.

The average daily volume at Location-2 is 1, 39, 108 Passenger Car Units (PCU). Peak-hour traffic is observed between 04:40 and 05:45 p.m. The percentage composition of weekday and weekend traffic is nearly identical, with two- and four-wheeler vehicles accounting for 68 percent of the total.

Model Development

The modeling procedure begins with the pre-processing of the data, which begins with data cleansing and input selection. As the ANN model can learn the pattern and assign weights accordingly, it is not necessary to eliminate the insignificant variables. A genetic algorithm (GA) is used to incorporate the most pertinent characteristics of the dataset into the neural network. This feature selection technique outperforms conventional methods and efficiently manages large data sets with numerous features.

One monthly dataset for January 2019 has been used for model training. The selected dataset is divided into training, validation, and test sets. The entire data set is separated into a training and test set with a 70:30 ratio. The test set is not utilized during the modeling procedure, but after the modeling, the procedure evaluates the model's ability to predict beyond the training dataset. The validation set is carved out from the training set at a ratio of 70:30 for hyper-parameter tuning.

This is followed by feature scaling of the dataset, and in this study, the 'Mean, and Standard Deviation Scaling Method' was chosen for feature scaling of input data using Eq. 1:

$$z = \frac{x - u}{s} \quad \ldots(1)$$

where 'x' is the observation, 'u' is the mean value, and 's' is the standard deviation. The 'sci-kit learn' package in python libraries was used for the feature scaling of the input data.

The list of meteorological and traffic characteristic variables parameters considered input variables include Temperature, Dew Point Temperature, Relative Humidity, Precipitation, Wind Direction, Wind Speed, Atmospheric Pressure, Mixing Height, Pasquill stability category, vehicular flow, vehicular composition. Five models with varying combinations of independent input variables and optimization algorithms were developed to determine the most accurate model. The most significant model for Location-1 is discussed in detail, and a summary of the remaining models for both locations is provided in Table 3.

Model-1

This model was created using the Python library's 'Keras' package. Temperature (temp), wind speed (wspd), traffic flow (tf), mixing height (mh), and atmospheric pressure (pa) were considered input variables (pres). On the input and output layers, the activation function is the identity function, while the activation function on the hidden layer is a hyperbolic tangent. The total number of hidden layers was identified so that the predicted hidden neurons on the test data set would yield the lowest prediction error. Several computational runs with random values of the number of neurons in hidden layers were performed for the model, and the combination yielding the minimum Mean Square Error after the network stabilizes and having satisfactory statistical performance (in terms of 'd' and RMSE) is considered to be the optimal number of neurons in the hidden layers. The trained ANN-based model network is saved at frequent intervals of training epochs, and its applicability is evaluated. The process continues until the performance of the trained model on the test dataset is optimal. After modeling with the selected hyper-parameters and plotting the mean absolute error of the training and test datasets, the number of epochs was determined. Early stopping was utilized to determine the optimal number of epochs. In this study, only a few hyper-parameters are optimized, while the rest are chosen theoretically. The activation function, learning rule, and batch size hyper-parameters were selected manually. The remaining hyper-parameters were optimized using the 'random search' algorithm in the 'Keras tuner' package from the Python libraries.

Table 2 depicts the interconnections between input, output, and hidden layers based on synaptic weights.

Table 3 displays the summary of model results indicating the significance of the model on the training dataset and its effectiveness on the testing dataset. Fig. 2 depicts a graph comparing observed and predicted values.

Tables 4 and 5 summarize the five distinct pollution models developed for this study.

The results of the modeling indicate that the combination of temperature, wind speed, mixing height, traffic flow, and atmospheric pressure produces the best model results for Location 1 and that the combination of temperature, wind speed, wind direction, relative humidity, mixing height, traffic flow, and atmospheric pressure produces the best

Table 2: Parameter estimates (Bias & Synaptic weights).

Predictor		Input layer						Output Layer
		(Bias)	temp	Wspd	tf	mh	pres	$PM_{2.5}$
Hidden Layer 1	H(1:1)	-0.27	-0.42	-0.17	-1.47	-1.22	0.41	0.03
	H(1:2)	4.77	0.17	1.00	0.88	1.50	-0.60	-2.13
	H(1:3)	3.85	-0.53	1.36	0.22	-0.11	-2.22	-1.57
	H(1:4)	2.14	0.40	0.52	0.28	-0.75	0.78	-1.39
	H(1:5)	0.07	-0.04	-0.30	0.86	-0.77	0.29	0.35
	H(1:6)	0.24	-0.05	-0.05	-0.29	0.22	-0.17	0.22
	H(1:7)	0.21	-0.39	-0.20	0.46	0.05	-0.35	-0.09
	(Bias)							4.59

Table 3: Model summary.

Model Significance			Independent & Normalized Variable Importance		
Training	Sum of Squares Error	71.20	temp	0.15	35.60%
	MSE	0.33	wspd	0.22	51.20%
	RMSE	0.57	tf	0.09	21.70%
	Relative Error	0.28	mh	0.12	28.60%
	Stopping Rule Used	100 consecutive step(s) with no error decrease[b]	pres	0.42	100.00%
Testing	Sum of Squares Error	28.12			
	MSE	0.13			
	RMSE	0.36			
	Relative Error	0.23			

b. Error computations are based on the testing sample.

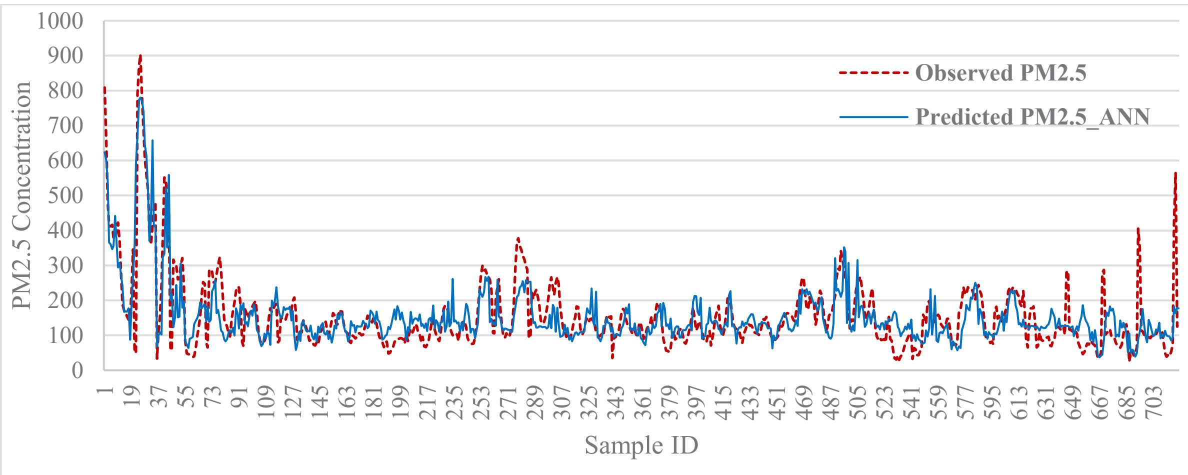

Fig. 2: Observed vs. Predicted $PM_{2.5}$.

model results for Location 2. In addition to the previous models, an ANN model was developed considering only traffic composition (Model 5). Still, the model predicted very poor results for both locations, indicating the inability of ANN models to account for the 'lag effect' in the absence of meteorological variables. Nevertheless, when considering traffic and meteorological variables, ANN can predict pollutant concentrations satisfactorily.

RESULTS AND DISCUSSION

Sensitivity Analysis

In addition, the model's sensitivity to reductions in traffic flow ranging from -5 percent to -20 percent was evaluated for both locations. Fig. 3 (Location-1) and Fig. 4 (Location-2) demonstrate that as traffic volume decreases, the pollutant concentration decreases as well increases, indicating that as traffic volume decreases beyond a certain threshold, the significance of the traffic variable in pollution prediction diminishes. Although pollution is predicted to increase as volume decreases, the predicted value of $PM_{2.5}$ is always less than or equal to the observed value.

The results concluded that a more than 20% reduction during peak hours would diminish the significance of the traffic variable, while the significance of background pollution would predominate at Location-1. Further, by decreasing traffic at the site by 20% during rush hour (10:30 am-11:30 am), the concentration of $PM_{2.5}$ pollutants could be reduced by 37%. Similarly, the results concluded that with a 9% reduction in traffic, the pollutant concentration could be reduced to 22% in the peak hours (16:45-17:45) at Location-2.

However, to achieve the $PM_{2.5}$ concentration specified by air quality standards, the predicted concentration must be reduced by an average of 88 percent during the peak hours for location-1 and 63 percent at Location 2. As a result, we can conclude that the contribution of background pollution is greater after a reduction in traffic volume of 20 percent for Location-1 and greater after a reduction in traffic volume of 10 percent for Location-2.

Table 4: Summary of model outputs for Location-1.

Input Layer		Model 1	Model 2	Model 3	Model 4	Model 5
		temp, wspd, t_flow, mixh, pres	temp, dwpt, rhum, wspd, pres, t_flow	temp, rhum, wspd, pres, t_flow	Mixh, temp, wdir, wspd, pres, rhum, t_flow	2w, 3w,4w, Goods, Bus, temp, wspd, mixh
Hidden Neurons		7	4	5	7	8
Transfer function		Hyperbolic tangent	Logistic	Hyperbolic tangent	Hyperbolic tangent	Logistic
Learning		Levenberg-Marquardt	Stochastic Gradient	Stochastic Gradient	Levenberg-Marquardt	Stochastic Gradient
Training	MSE	0.32	0.42	0.36	0.02	0.73
	RMSE	0.57	0.65	0.6	0.14	0.86
	Relative Error	0.28	0.37	0.32	0.31	0.64
Testing	MSE	0.13	0.12	0.19	0.01	0.59
	RMSE	0.36	0.35	0.43	0.11	0.77
	Relative Error	0.23	0.45	0.39	0.28	0.55
	d	0.82	0.76	0.78	0.75	0.61
	R^2	0.74	0.62	0.66	0.56	0.42

Table 5: Summary of Model Outputs for Location-2.

Input Layer		Model 1	Model 2	Model 3	Model 4	Model 5
		temp, wspd, t_flow, mixh,pres	temp, dwpt, rhum, wspd, pres, t_flow	temp, rhum, wspd, pres, t_flow	Mixh, temp, wdir, wspd, pres, rhum, t_flow	2w, 3w,4w, Goods, Bus, temp, wspd, mixh
Hidden Neurons		6	6	5	9	11
Transfer function		Hyperbolic tangent	Logistic	Hyperbolic tangent	Hyperbolic tangent	Logistic
Learning		Levenberg-Marquardt	Stochastic Gradient	Stochastic Gradient	Levenberg-Marquardt	Stochastic Gradient
Training	MSE	0.08	0.28	0.45	0.13	0.35
	RMSE	0.29	0.53	0.67	0.37	0.59
	Relative Error	0.19	0.42	0.45	0.24	0.31
Testing	MSE	0.1	0.42	0.67	0.05	0.12
	RMSE	0.31	0.65	0.82	0.22	0.34
	Relative Error	0.2	0.36	0.42	0.19	0.49
	d	0.89	0.75	0.71	0.91	0.66
	R^2	0.8	0.65	0.62	0.81	0.59

The results concluded that under open terrain conditions, i.e., Location-2, the significance of the traffic variable in its association with $PM_{2.5}$ is almost half the significance observed under built-up conditions for Location-1. Also, in terms of $PM_{2.5}$ reduction, the maximum reduction observed at Location-1 (surrounding built-up environment), and Location-2 (open terrain surrounding environment) is 1.85 and 2.44 times the percent reduction in traffic during peak hours, respectively. Hence, it can be concluded that the surrounding built environment has a significant role in influencing pollution dispersion, and appropriate actions must be taken to reduce the overall amount of background pollution (Gupta et al. 2020).

CONCLUSIONS

Most of the research carried out in the previous decade related to vehicular pollution modeling was based on deterministic (particularly plume-based dispersion model) and statistical approaches. These methods do not fully reflect the complex and non-linear relationships between the variables. As a result, the ANN approach ought to be investigated further to investigate the intricate interrelationships between urban traffic, climatological factors, and other types of pollutants. In addition, the creation of a dependable vehicular pollution model could assist local authorities in the development of effective strategies for the management of air quality.

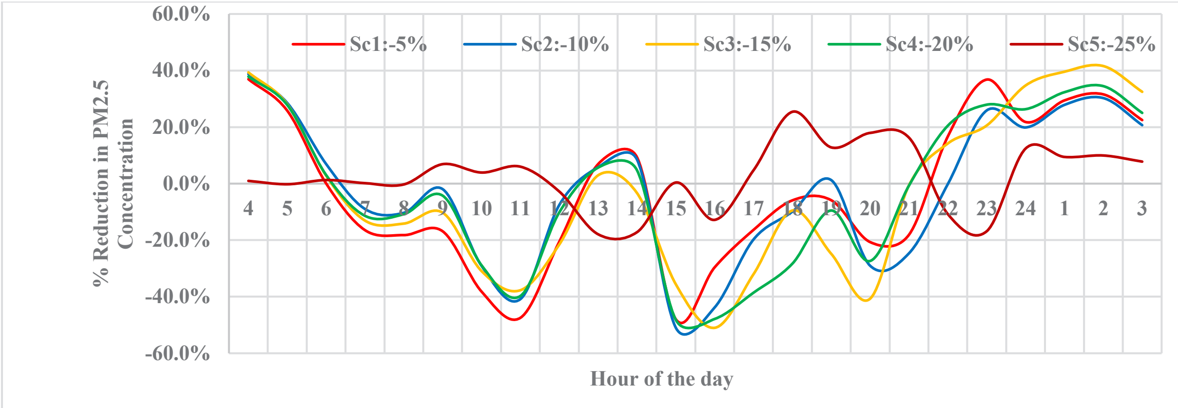

Fig. 3: % Reduction in $PM_{2.5}$ concentration with reduction in traffic volume for Location-1.

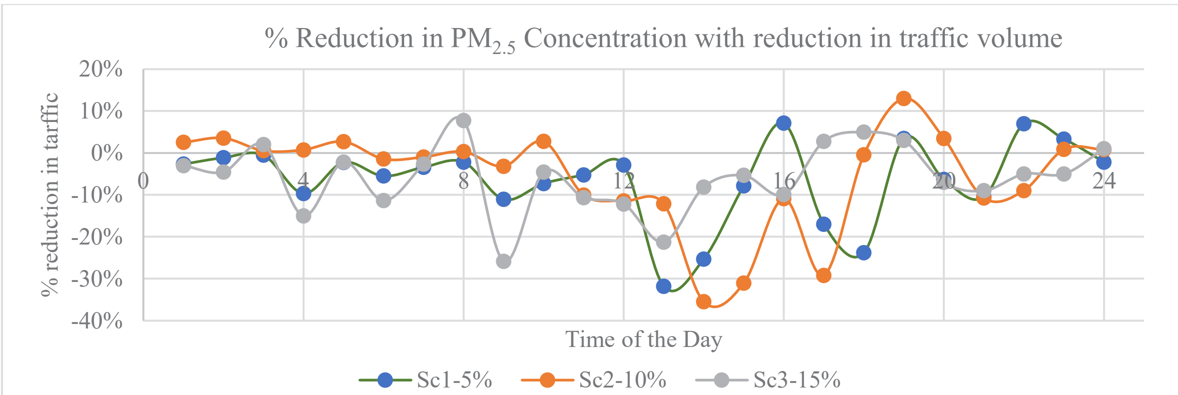

Fig. 4: % Reduction in $PM_{2.5}$ concentration with reduction in traffic volume for Location-2.

The ANN approach has predicted satisfactory results for vehicular pollution modeling in this study. Nevertheless, additional traffic variables, such as composition, speed, fuel type, and so on, seasonal variations, and the impact of the physical environment, need to be investigated further.

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