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Original Research Article

APPLICATION OF M5P MODEL TREE AND ARTIFICIAL NEURAL NETWORKS FOR TRAFFIC NOISE PREDICTION ON HIGHWAYS OF INDIA

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A b s t r a c t

Traffic noise prediction is the fastestgrowing development that reflects the rising concern of noise as environmenta l pollution. Prediction of noise exposure levels can help policy makers and government authorities to make early decisions and plan effective measures to mitigate noise pollution and protect human health. This study examines the application of M5P model tree and Artificial Neural Network (ANN) for prediction of traffic noise on Highways of Delhi. In total 865 data sets collected from 36 sampling stations were used for development of model. Effects of 13 independent variables were considered for prediction. Model selection criteria like determination coefficient (R^2), root mean square error (RMSE), Mean absolute error (MSE) are used to judge the suitability of developed models. The work shows that both the models can predict traffic noise accurately, with R^2 values of 0.922(M5P), 0.942(ANN) and RMSE of 2.17(M5P) ,1.95(ANN). The results indicate that machine learning approach provides better performance in complex areas, with heterogenous traffic patterns. M5p Model tree gives linear equations which are easy to comprehend and provides better insight, indicating that M5P model trees can be effectively used as an alternative to ANN for predicting traffic noise.

Key words: machine learning, M5P model tree, artificial neural networks, traffic noise

1. INTRODUCTION

Transportation is very essential for developing cities; however, its negative consequences are overshadowed by its benefits. Traffic noise is inevitable for urban regions and its impact on the environment is constantly growing. Many studies on assessment of noise pollution have been conducted for various cities of the world [1-7] and clearly indicates the discomfort and annoyance level faced [8]. Noise has become pervasive and penetrated our lives severely. Noise effects human health in different

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ways depending on the intensity and exposure- physical effects like hearing impairment; physiological effects like increased heartbeat, increased blood pressure, cardiovascular disease, ulcer etc; psychological effects include insomnia, annoyance, stress etc; performance effects like reduction in output, misunderstandings etc [9-11]. World Health Organization (WHO) declared noise as the second largest environmental cause of health problems after air pollution (particulate matter) (WHO 20146).

Contribution of traffic noise is more significant in comparison to commercial and industrial activities towards urban noise pollution [12]. The severity of traffic noise pollution is going to increase in future. Therefore, it is necessary to investigate noise pollution from transportation point of view for formulating and implementing suitable strategies to combat traffic noise pollution. For controlling noise pollution in urban environment, it is necessary to develop methods to predict traffic noise. The first traffic noise prediction (TNP) models date back to early 1950s. Since then, a large number of TNP models have been developed using various approaches like statistical land use regression model, machine learning model and Numerical acoustic models [13]. Land use regression(LUR) models require geospatial data to predict noise levels for different locations within study area[14]. Xie et al. [15] developed LUR model for Dalian municipality. Ragettli et al. [16] gave LUR model for Montreal, Canada. An open-source GIS based model for Leicester and Norwich (British cities) was developed by Gulliver et al. [17]., Fallah-Shorshani et al.[13] included rail, road and aircraft noise in a LUR model for Toronto City, Canada.

Acoustical models are most popular in estimating noise. These models include numerical equations based on road geometry and traffic conditions, considering sound propagation, refraction and absorption. Many countries have developed their own TNM and considered them satisfactory. Federal Highway Administration (FHWA) model was developed for USA by Barry and Regan, 1979[18]. CORTN, Calculation of Road Traffic Noise Model model was developed for the Department of Transport, UK. The multisource Harmonoise model for Europe [19], and RLS 90 for Germany, ASJ RTN 2008 for Japan, CNOSSOS-EU for Europe. Garg and Maji [20] presented the review of these principal traffic noise models.

Currently numerous machine learning approaches are used and applied for prediction such as artificial neural networks (ANNs), Generalised linear model (GLM), Random Forest model (RF) and Decision trees etc [21-22]. Machine-Learning Algorithms are more reliable substitute to linear regression due to their non-linearity modelling capacity [23]. Comparison of these methods with multiple linear regression has shown better outputs in terms of prediction accuracy [24]. Mostly used models that have shown exciting potential in the field of traffic noise predictions are Random Forests and ANN [25]. However, algorithm-based models require large datasets for generalization and nonlinear mapping. These models are better in prediction but, not able to quantify the effect of variables influencing the noise levels [26].

The focus of current study is to assess the applicability of M5P tree model, a machine learning approach in predicting traffic noise for heterogeneous traffic conditions. Latest research studies in other fields have suggested successful employment of M5P tree model [27-30] which provides simple linear equations for prediction at each node, which help the user to identify the factor affecting the modelling output.

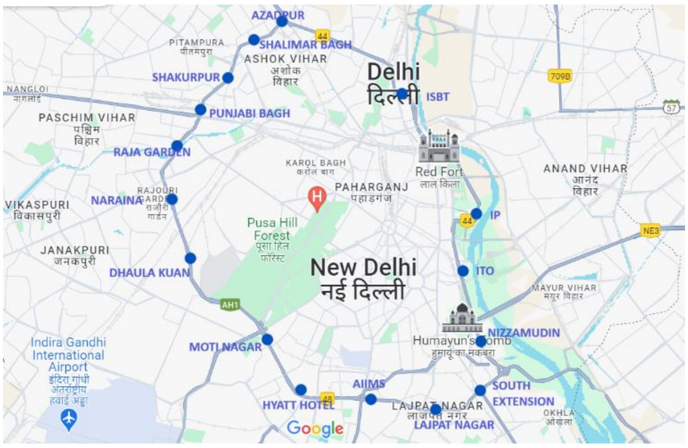
Use of M5P model Tree for traffic noise prediction is yet to be explored by the researchers. This study is possibly the first one in which the application of M5P model tree for TNP is evaluated. A brief overview and practicality of M5P tree are provided in the methodology section. Therefore, this examines the effectiveness of two soft computing techniques, M5P and ANN, for estimating the traffic noise and to identify the key factors responsible for traffic noise.

2. METHODOLOGY

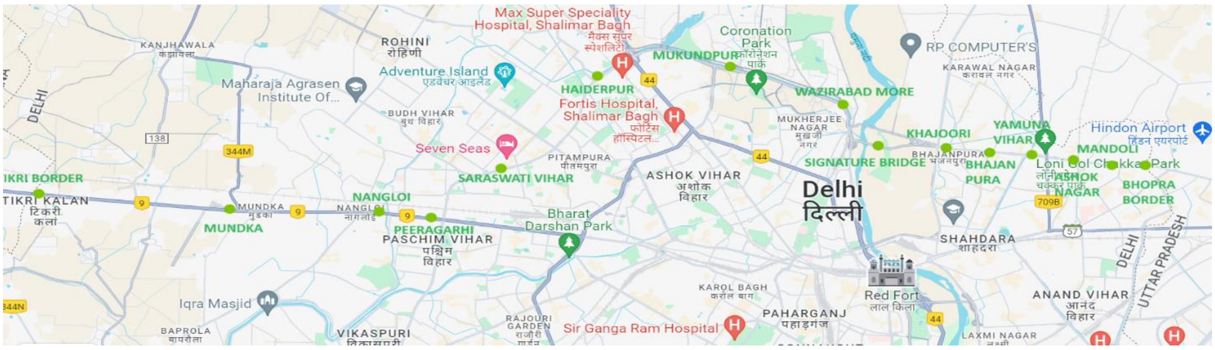
2.1. Study area

Delhi is a city and a union territory of India . It is the largest city of India with an estimated population of 31,181,377 in 2021 [31] with total area of 1484 km^2 governed by Municipal corporation of Delhi. Delhi is progressing continuously since independence and rapid urbanization of Delhi is forcing working population to commute in the city. So, a large number of vehicles need to be circulated in the city to meet their commuting requirements.

The present study involves measurements and analysis of traffic noise pollution on NH-9 (National Highway) and Ring Road (State Highway) of Delhi city, India during summer and winter season from July 2022 to February 2023. In total 36 sampling points were selected including 30 segments and 6 intersections (shown in figure 1). Sampling stations on NH-9 are marked in green colour and stations on Ring Road marked in blue.



(a)



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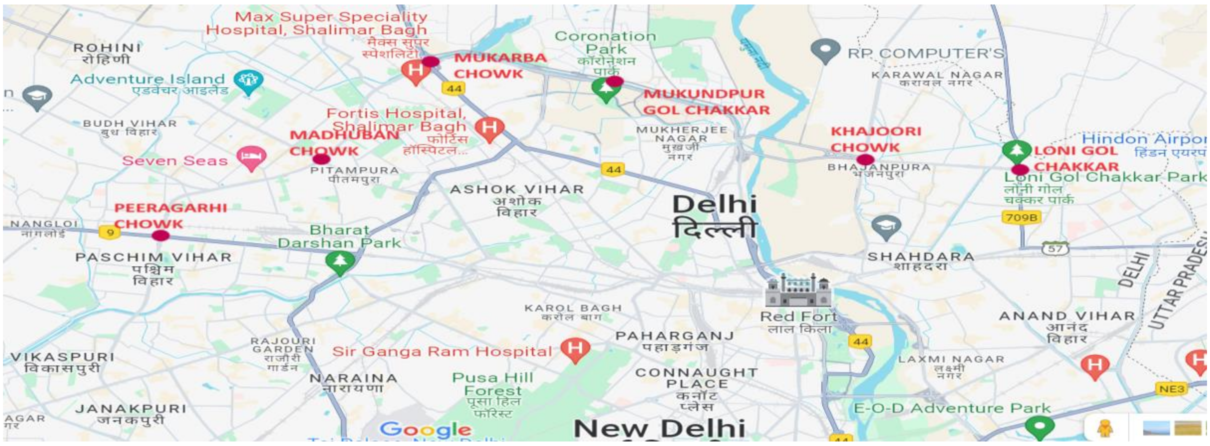

(c)

Fig.1. Geographical locations of sampling stations on google map a) Ring Road Segments b) NH-9 segments c) Intersections

2.2. Choice of variables and data sets

Choice of explanatory variables depended on variables declared significant in previous studies and reliable measurement technique [32-37]. In present study, the variables considered are traffic volume (Q), Percentage of two-wheeler (2W. perc), percentage of three wheelers (3W. perc), percentage of four wheelers (4W. perc), percentage of heavy vehicles (HV. perc), average speed of vehicles (V), speed variance (VAR), Temperature (Temp), Wind speed (WS), Humidity (RH), Number of lanes(L), International roughness index (IRI) and average building height (ABH). 864 data sets of different variables and Leq5min were used for the model development. For ANN, SPSS software and for M5P tree WEKA software is used. For both models 70% data used for training and 30% for validation. Summary of all variables collected from different sites are provided in table 1.

Table 1. Model variables descriptive statistics

S.No	Variable Designation in model	Measurement unit	Minimum	Maximum	Mean	Std. deviation
1	Leq 5min (Dependent variable)	dBA	51.77	77.92	65.32	5.57
2	2W. perc	%	21.84	70.74	39.99	10.70
3	3W. perc	%	5.93	34.23	16.30	5.47
4	4W. perc	%	15.64	63.00	38.59	11.15
5	HV. perc	%	0.80	24.47	5.08	3.00
6	Q	Vehicles/ 5 min	143	869	452.29	154.52
7	Average speed of vehicles (V)	Km/h	15.63	63.72	46.35	10.18
8	VAR	Km/h	0.87	102.26	11.65	15.06
9	L	Numbers	3.00	5.00	3.73	0.55
10	IRI	M/Km	4.01	15.03	7.47	2.34
11	ABH	Meters	0.00	17.50	8.09	6.47
12	Temp	Degree Celsius	7.00	40.00	32.32	2.83
13	WS	Km/h	3.00	19.00	10.27	4.13
14	RH	%	8.00	90.00	65.94	12.71

2.3. Noise data monitoring

SD card real time data Recorder, USB/RS232 SOUND LEVEL METER Model: SL-4033SD was used for measuring noise levels. Sound level meter was installed at a distance of 1meter from road edge and at a height of 1.5 meter on a tripod stand (shown in figure 2 and 3) to reduce the error due to reflection of sound from the body. Monitoring was conducted for one hour in morning (between 9:00am to 11:00 am) considered to be rush hours in Delhi and for one hour in afternoon (between 1:00 pm to 3:00pm) considered non rush hours on working days (Monday to Friday). SLM was calibrate at each monitoring site and noise data was recorded with sampling rate of 1 sec. Statistical Analysis tools were used for data processing and analysis. Since atmospheric conditions such as wind speed, temperature and relative humidity have significant effects on noise levels [38] these factors were measured on site simultaneously using AccuWeather app. 5 min equivalent noise levels were determined and 24 data sets of Leq 5min from each site were collected.

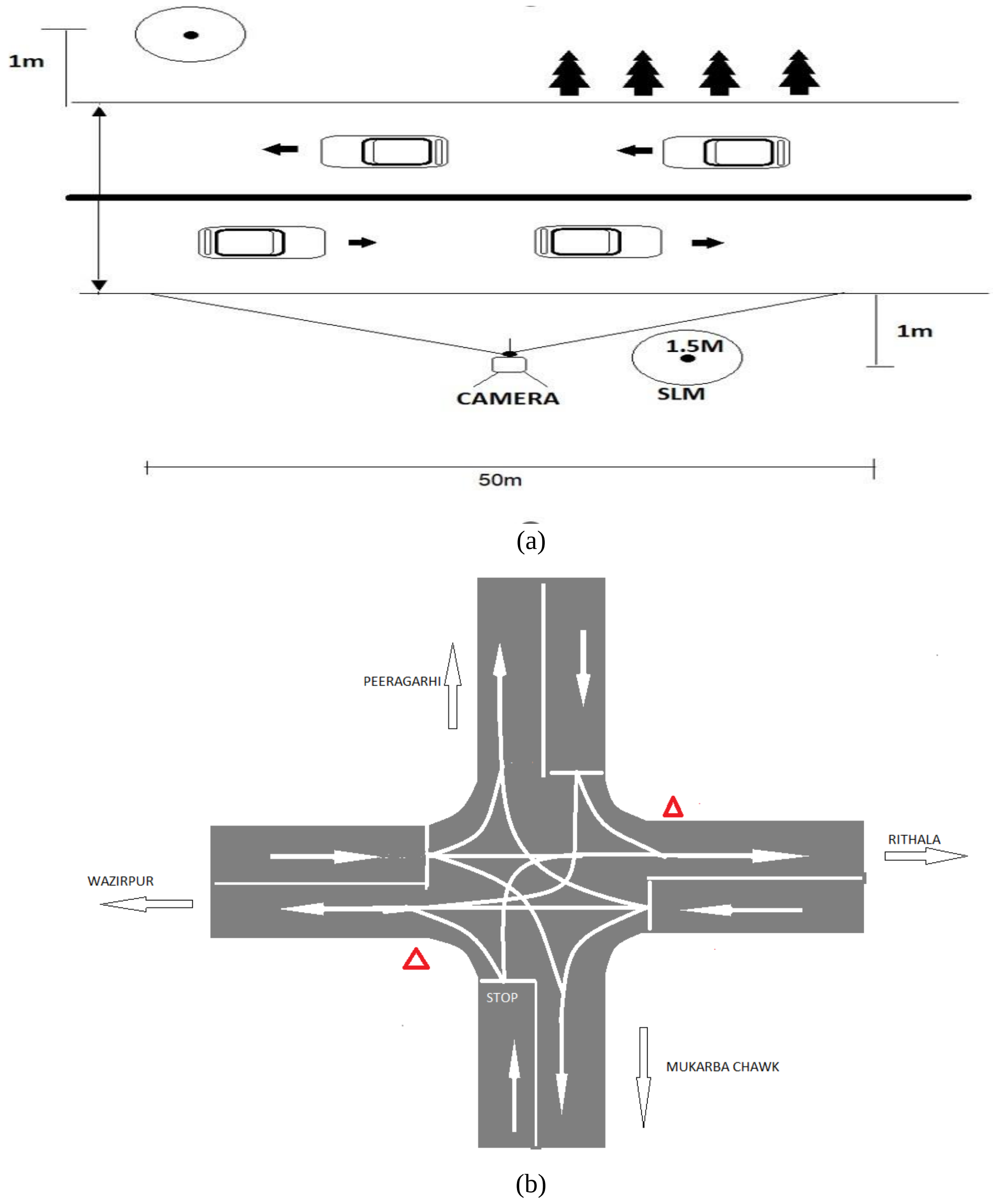

Fig. 2. Sampling plots for (a) segments and (b) intersections

2.4. Traffic data monitoring

Traffic related data were determined from videos recorded on site simultaneously with noise measurements (shown in figure 3). Traffic volume at 5-min time intervals, and traffic composition were collected from video. Vehicles were divided in four different categories: -

2Wheelers—Bikes and scooters

3Wheelers- Auto, E rickshaw and Small Tempo

4Wheelers-cars, vans, Jeeps, and small commercial vehicles

Heavy Vehicle-Bus and heavy vehicles.

The average traffic speed was also obtained from videos. Marking of 15m distance was done on the road and the time required by vehicle to cover this distance was recorded by counting the number of frames using frame capture application. Mobile app Road Bump Free was used to record international roughness index. Figure 3 represents the SLM location on site for segments and intersections (marked with red triangle).

Fig. 3. Image showing SLM and camera installed at site

2.5. M5P Tree Model

M5P algorithm are based on M5 algorithm which was originally developed by the Quinlan [39] involving the decision trees and multilinear regression. Decision trees are used for classification of input and output to provides the regression equation giving relationship between data. It generally works in three steps. (i)Building a model tree. (ii)Pruning tree (iii) Smoothing step. In first step decision trees are build using splitting criterion. The splitting procedure stops when variation of instances is very slight or only few instances are remaining, expected error at each node is reduced by standard deviation reduction factor [40]. Second step involves pruning back the tree from each leaf to delete the error occurred in learning data. In last step all leaf models are combined from leaf to root to form the final pruning tree which can create discontinuities among the linear models. Therefore, smoothing is done to avoid this problem.

2.6. Artificial Neural Networks

The idea of neural networks came from the perceptron model developed in the 1950s [41]. ANNs imitates the human brain [42]. Multilayer perceptron is a feedforward ANN that consists of three layers input layer, hidden layer, and output layer. A multilayer perceptron with single hidden layer is called the shallow neural network and with more than one hidden layer is known as deep neural network [42]. Artificial neurons(nodes) are the processing elements of neural networks, Signal is transmitted through these nodes from input-hidden-output layer. According to chosen activation function each node receives the input signal and produce the output signal [43]. The learning algorithm is the process of continuously updating the connection weights of the neurons in the hidden layers to minimize the differences between the target and output samples [44].

3. RESULTS AND DISCUSSIONS

Data collected from all sampling sites was analysed for the seasonal and diurnal variations. Since the monitoring was done in two parts during summers and winters. First part of monitoring was in the month of July and August 2022 and second part was in the month of January and February 2023 results shown in figure 4(Chart A&B). For diurnal analysis data was monitored at two different times of the day results presented in Figure 4(Chart C& D). From Chart A and B of figure 4, it is observed that noise levels are observed to be more during winters in comparison to summers, during rush hours as well as off rush hours. Seasonal variation revealed that traffic noise levels in around 90% of sampling sites increased in winters from summers. Reason for this can be the temperature inversions in winters as the air near the ground is cooler than the layer of air above, trapping the cooler air near the roads, acting like the cover and trapping the sound energy waves and stopping them from proper dispersion making the roads noisier. On the other hand, in summers as temperature is more and as it is evident noise travels with the transfer of energy from one molecule to another, this transfer of energy among the molecules would be more due to the increased temperature, hence the dispersion of noise is predominant in summers.

Figure 4 chart C & D represents the diurnal variation of LAeq 1hr at different sampling stations during rush hours and off rush hours, in winters and summer season. Significant variation between noise levels of rush hours and off rush hours are not observed, may be due to more commercial vehicles plying on road during off rush hours. Spatial analysis of noise levels indicates that noise levels at around 73 % of sampling locations are exceeding the acceptable limits. Maximum noise levels were observed at Bhopra Border, Ashok Nagar and Shalimar Bagh, all three being the commercial areas are exceeding the CPCB (Central Pollution Control board) limit of 65 LAeq for day time by 15 dBA. Noise level of silent zones like AIIMS was 21 dBA higher than the prescribed limit of 50 dBA.

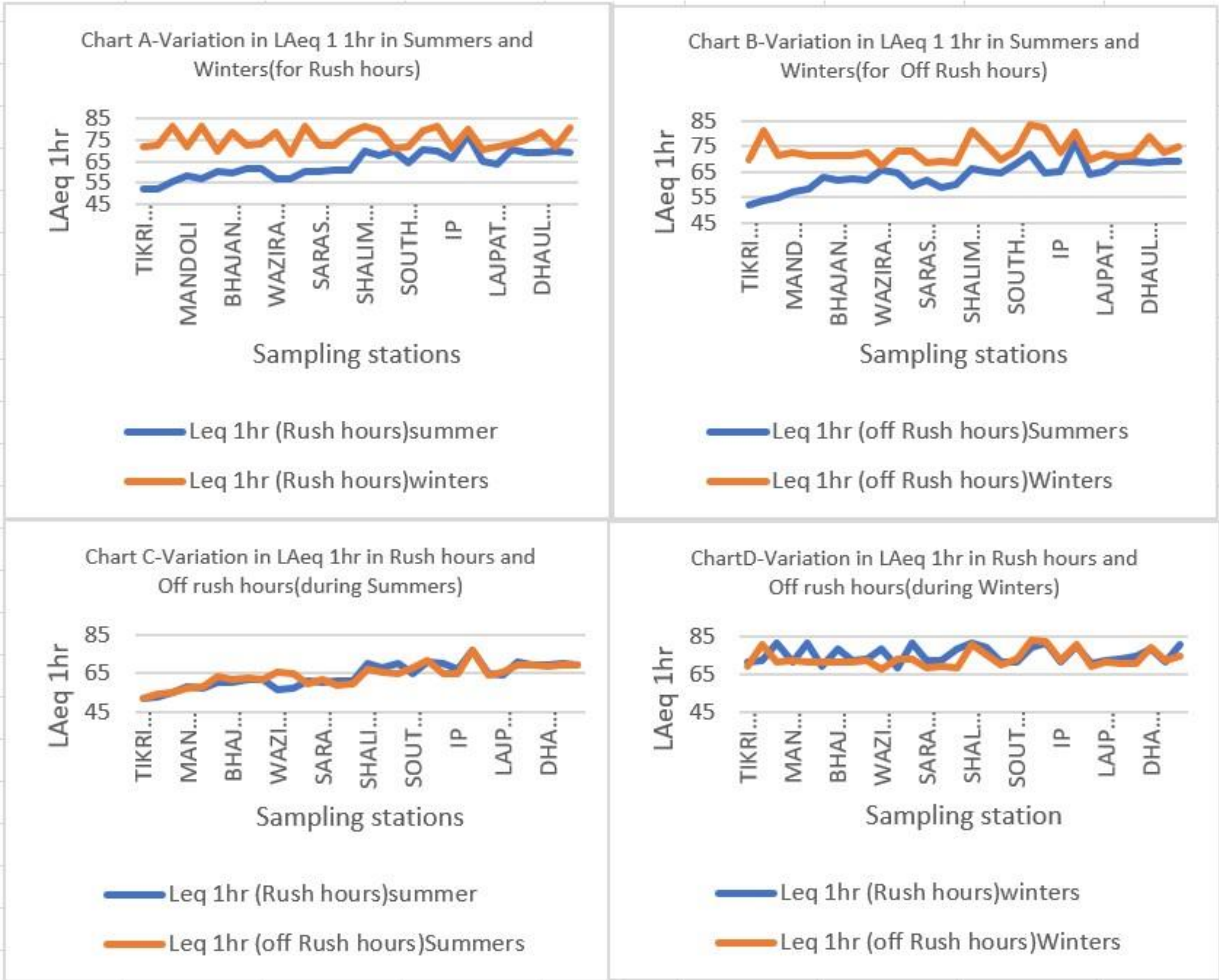

Fig. 4. Seasonal and diurnal variation in noise levels

3.1 Traffic noise prediction

The R^2, RMSE and MAE values of M5P model tree and ANN model for predicting traffic noise are provided in table2. It can be seen from table 2 that ANN model out performed M5P model tree in terms of all the three indices. However, M5P model tree also provided a good fit with R^2=0.922. Moreover, it provided simple linear equations.

Table 2. Performance metrics of developed models

Model	R^2	RMSE (dBA)	MAE (dBA)
M5P tree	0.922	2.17	1.67
ANN	0.942	1.95	1.154

Outputs of M5P model tree is provided in Figure 5 and traffic noise prediction equations are given in figure 6, these equations can be used to predict traffic noise with variables within range provided in figure 5. Tree is structured from top to down representing the actual tree from root to leaves. These topmost levels in tree are the most important parts for final prediction. In figure 5 the developed tree has 14 end nodes. Each end node provides information about the node, as in the leaf 1 LM1(124/38.344%), 124 are the instances and the 38.344 % is the root relative squared error. The linear regression (in figure 5) is indicated at each leaf.

The first division is based on the most significant variable i.e traffic volume. International roughness index (when Q< 534.5) and percentage four-wheeler (when Q>534.5) are the second criteria used for splitting and therefore second most important variables, and so on. Thus, M5P model tree in figure 4 shows that traffic volume, road roughness, average building height, percentage of 4Wheelers, speed variance and no of lanes are most significant variables. These results are similar to the findings reported in literature [45-47].

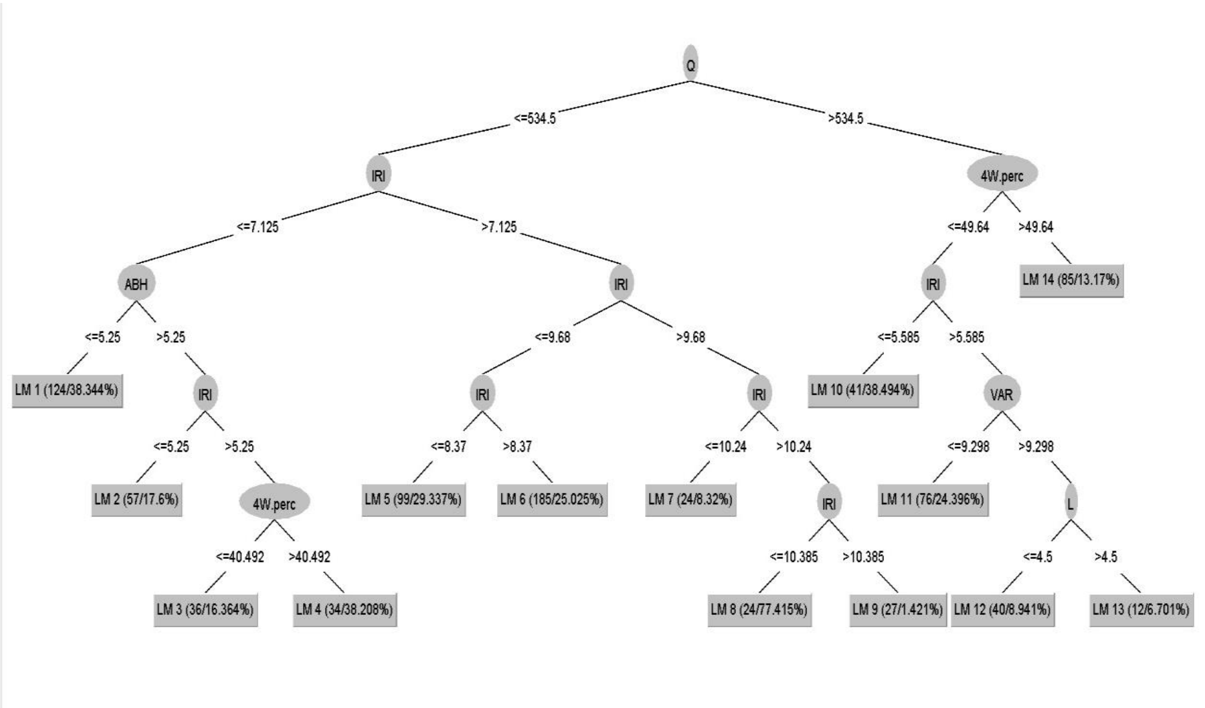

Fig. 5. M5P tree model algorithm for trained data sets

14 linear models LM1-LM14 are given in figure 5 and each model equation can be used for different set of conditions like LM1 can be used for prediction when traffic volume is less than 534.5 and IRI is less than 7.125m/Km and average building height is less than 5.25m[48].

Traffic volume, Percentage of four wheelers and international roughness index are found to be significantly associated with traffic noise. Traffic noise was found increasing with increase in traffic volume and IRI especially when variance of vehicle speeds is high and no. of lanes was below 4(LM12). Traffic noise is also associated with increase in traffic volume and percentage four-wheeler (LM14). From LM4 it as clear that traffic noise is increasing with increase in average building height and road roughness when percentage of four-wheeler is more. IRI have significant effect on traffic noise on roads with low traffic volume and on roads with heavy traffic volume, percentage 4 wheelers have shown significant effect. Percentage of heavy vehicles is positively associated with noise levels on roads with low traffic volume whereas it is negatively associated on roads with high traffic volume.

Multilayer perceptron neural networks were used in the present work. The specifications of developed Artificial Neural Networks model are given in table 3. Hyperbolic tangent is the activation function used for hidden layers and identity activation function is used for outer layer. Figure 7 describes the ANN design with two hidden layers, one input layer with ten independent variables and one output layer. 7 units are included in each hidden layer.

As per model summary, sum of square error for training data sets and testing data sets are observed 1.82 and 3.81, while the relative error obtained is 0.04 for training data sets and 0.21 for test data. Using developed network, the model can predict Leq value for testing dataset using weights computed for trained datasets.

Table 3. ANN model specifications

Input layer	No of Units	13
	Rescaling method of covariates	standardized
Hidden layer	Number of Hidden Layers	2
	Number of Units in Hidden Layer 1[a]	7
	Number of Units in Hidden Layer 2[a]	7
	Activation Function	Hyperbolic tangent
Output layer	Dependent Variables	Leq 5min
	Number of Units	1
	Rescaling Method for Scale Dependents	Standardized
	Activation Function	Identity
	Error Function	Sum of Squares

a. Excluding the bias unit.

LM num: 1

Leq 5min = -0.0786 * 2W. perc + 0.0295 * 3W. perc + 0.0283 * 4W. perc + 0.005 * HV. perc + 0.0089 * Q + 0.0123 * V + 0.0023 * VAR - 0.1106 * L + 0.1873 * IRI + 0.0577 * ABH - 0.5855 * Temp - 0.1743 * RH + 88.5743

LM num: 2

Leq 5min = 0.005 * 2W.perc + 0.0295 * 3W.perc + 0.0283 * 4W.perc + 0.005 * HV.perc + 0.0072 * Q + 0.0578 * V + 0.0023 * VAR - 0.1106 * L + 0.5763 * IRI + 0.0568 * ABH - 0.0372 * Temp - 0.0132 * RH + 55.8916

LM num: 3

Leq 5min = 0.005 * 2W.perc + 0.0295 * 3W.perc - 0.0017 * 4W.perc + 0.005 * HV.perc - 0.0026 * Q + 0.0218 * V + 0.0023 * VAR - 0.1106 * L + 0.5161 * IRI + 0.0568 * ABH - 0.0372 * Temp - 0.0132 * RH + 65.7356

LM num: 4

Leq 5min = 0.005 * 2W.perc + 0.0295 * 3W.perc - 0.0029 * 4W.perc + 0.005 * HV.perc - 0.0026 * Q + 0.0218 * V + 0.0023 * VAR - 0.1106 * L + 0.5161 * IRI + 0.0568 * ABH - 0.0372 * Temp - 0.0132 * RH + 64.2323

LM num: 5

Leq 5min = 0.0067 * 2W.perc - 0.0194 * 3W.perc + 0.0228 * 4W.perc + 0.005 * HV.perc + 0.0008 * Q + 0.0253 * V + 0.0023 * VAR - 0.1318 * L + 0.3996 * IRI + 0.921 * ABH + 0.6462 * Temp - 0.0135 * RH + 23.1312

LM num: 6

Leq 5min = 0.0067 * 2W. perc + 0.0249 * 3W.perc + 0.0228 * 4W.perc + 0.005 * HV.perc + 0.0037 * Q + 0.0774 * V + 0.0023 * VAR - 2.7402 * L - 3.3617 * IRI - 0.5248 * ABH + 0.0205 * Temp - 0.0682 * RH + 100.635

LM num: 7

Leq 5min = 0.0067 * 2W.perc + 0.0213 * 3W.perc + 0.0228 * 4W.perc + 0.005 * HV.perc + 0.001 * Q + 0.0241 * V + 0.0023 * VAR - 0.2561 * L + 0.1987 * IRI + 0.0458 * ABH + 0.0656 * Temp - 0.0082 * RH + 63.5324

LM num: 8

Leq 5min = 0.0067 * 2W.perc + 0.0213 * 3W.perc + 0.0228 * 4W.perc + 0.005 * HV.perc + 0.001 * Q + 0.0241 * V + 0.0023 * VAR - 0.2561 * L + 0.5432 * IRI + 0.0458 * ABH + 0.0656 * Temp - 0.0082 * RH + 51.686

LM num: 9

Leq 5min = 0.0067 * 2W.perc + 0.0213 * 3W.perc + 0.0228 * 4W.perc + 0.005 * HV.perc + 0.001 * Q + 0.0241 * V + 0.0023 * VAR - 0.2561 * L + 0.5185 * IRI + 0.0458 * ABH + 0.0656 * Temp - 0.0082 * RH + 54.9336

LM num: 10

Leq 5min = 0.0029 * 3W.perc + 0.0273 * 4W.perc - 0.0143 * HV.perc - 0.0063 * Q + 0.0009 * V + 0.0146 * VAR + 0.215 * L + 0.0618 * IRI + 0.0165 * ABH + 0.0026 * Temp + 0.3812 * WS + 57.2531

LM num: 11

Leq 5min = 0.0029 * 3W.perc + 0.0273 * 4W.perc - 0.0143 * HV.perc + 0.0007 * Q + 0.0068 * V + 0.0143 * VAR + 0.183 * L + 0.2205 * IRI + 0.0165 * ABH + 0.0026 * Temp + 0.019 * WS + 56.5265

LM num: 12

Leq 5min = 0.0029 * 3W.perc + 0.0273 * 4W.perc - 0.0143 * HV.perc - 0.0065 * Q + 0.0445 * V + 0.0159 * VAR + 0.4464 * L - 0.0108 * IRI + 0.0165 * ABH + 0.0026 * Temp + 0.019 * WS + 60.7189

LM num: 13

Leq 5min = 0.0029 * 3W.perc + 0.0273 * 4W.perc - 0.0143 * HV.perc - 0.0065 * Q + 0.028 * V + 0.0159 * VAR + 0.6933 * L - 0.0108 * IRI + 0.0165 * ABH + 0.0026 * Temp + 0.019 * WS + 61.1872

LM num: 14

Leq 5min = 0.0029 * 3W.perc + 0.0323 * 4W.perc - 0.2777 * HV.perc - 0.0086 * Q + 0.0009 * V + 0.0087 * VAR + 0.0827 * L - 0.0402 * IRI + 0.0165 * ABH + 0.0026 * Temp + 0.0164 * WS + 66.956

Fig. 6. Traffic noise prediction equations given by M5P tree Model

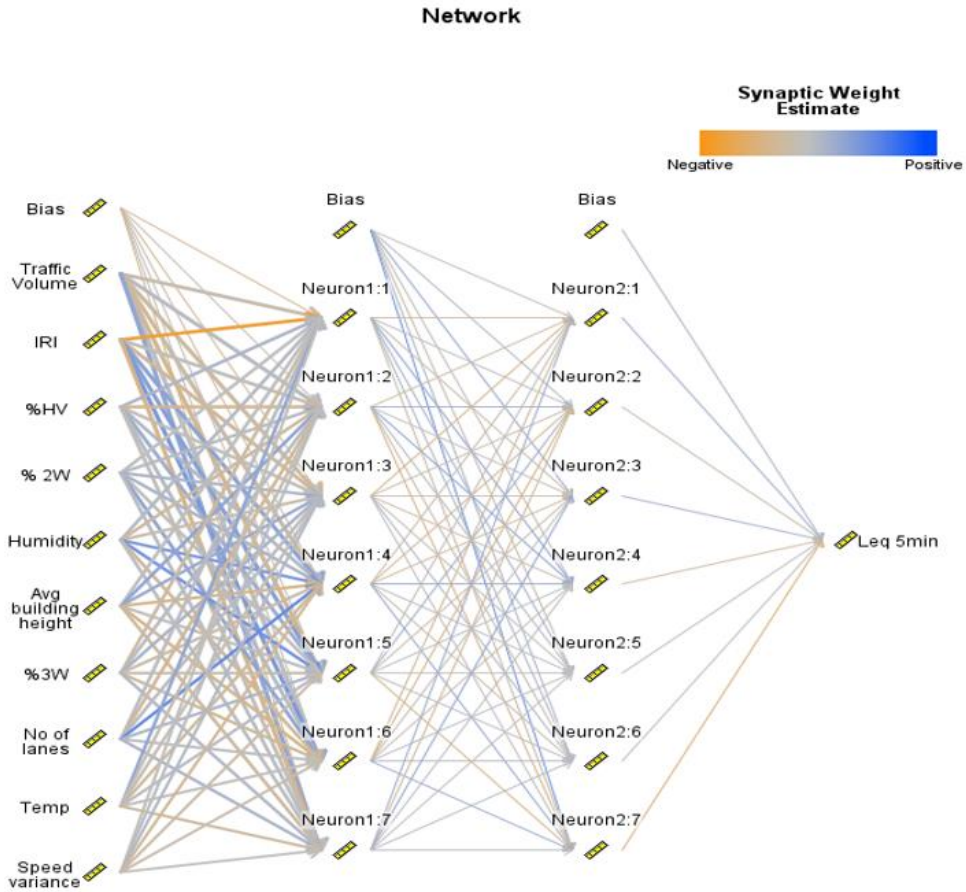

Fig. 7. The neural network diagram of the ANN model

The network displayed in Figure 7 with two hidden layers indicate that all independent variables are contributing either positively or negatively or in both ways, with different strengths to the neurons present in the first hidden layer. The robust positive influence is shown by the IRI to the neuron 1:4,1:5 and 1:6 of first layer. Great positive influence of number of lanes to neuron 1:4 and traffic volume to neuron 1: 7 can also be seen. The strongest negative influence is seen from the variable IRI to the neuron 1:1 of first layer. Neurons of first hidden layers are contributing both positively and negatively to the neurons of second hidden layers.

Traffic volume, IRI and % of Heavy vehicles are found to be most significant predictor of Leq in ANN. A comparison of results from available literature indicates similar trends. Effect of traffic volume on traffic noise are in accordance to studies reported by Halim and Abdullah [49]. Tandel and Macwan [50] and Kamineni et al [51] confirms heavy traffic highways have higher noise levels. Wei et al [52] in their study confirmed that increase in IRI increases the corresponding noise levels on roads. Kamandang et al. [53] concluded, heavy vehicles have 70 to 80 percent influence on noise pollution in West Surabaya, Indonesia.

Figure 8 represents the scattered plot of observed and predicted values of L_{eq} for testing data sets of both the models, clearly indicating that ANN model has superior predictive power. M5P model provide different significant variable for different types of roads whereas ANN provide no such differentiation for different roads. ANN needs trial and error method to find the number of hidden layers and number of nodes whereas the M5P model tree provide understandable equations. M5P model tree have high processing speed in comparison to ANN model (a time-consuming approach).

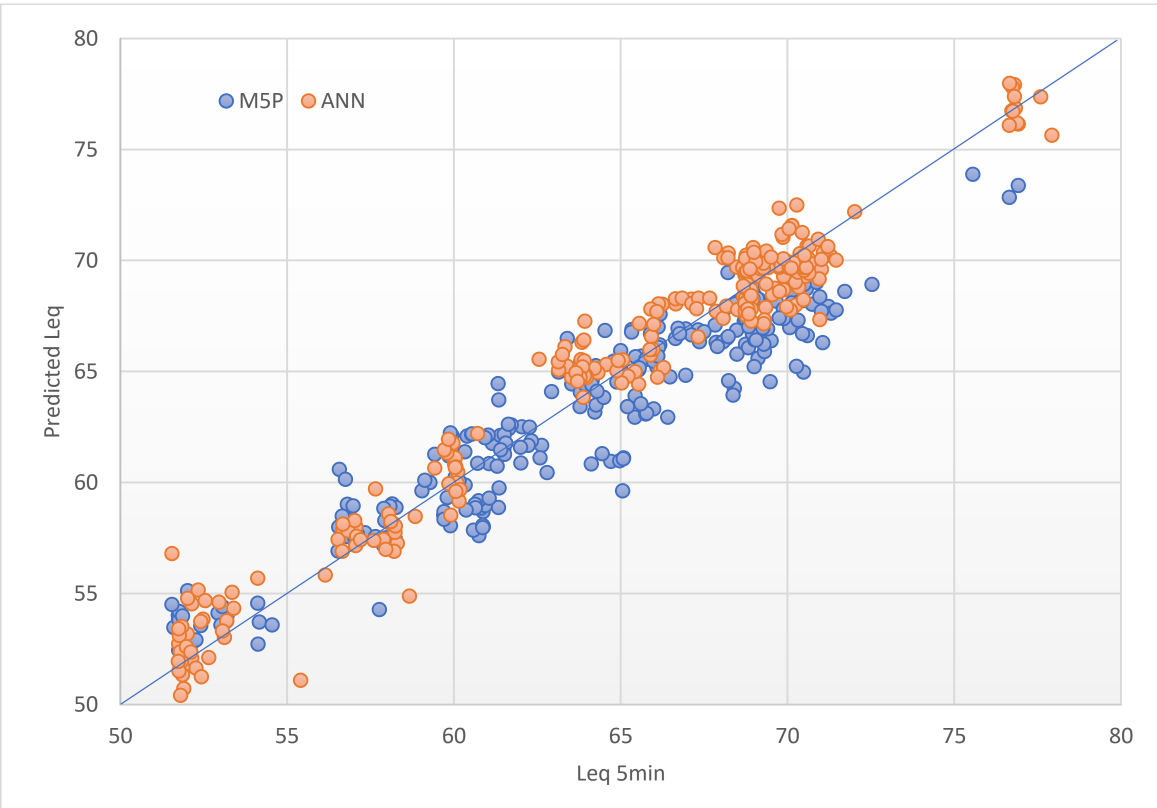

Fig. 8. Predicted versus observed values plot for M5P model tree and ANN Model for test data sets

4. CONCLUSION

The main goal of this study was to compare the ability of M5P model tree and ANN Model to predict traffic noise and identify the main factors affecting traffic noise. Dataset comprising 864 data from 36 sampling stations, using field measurements were collected from National and State highways located in

Delhi. Both M5P model tree and ANN were found to predict traffic noise significantly well, with acceptable (R^2) values of 0.922 (M5P) and 0.942 (ANN). M5P model tree considered Average building height, IRI, perc. 4Wheeler as significant predictors of traffic noise for roads with traffic volume < 534.5/5min and perc. 4Wheeler, IRI, speed variance, no of lanes for roads with traffic volume > 534.5. ANN considered Traffic volume, IRI and percentage of heavy vehicle as most effective predictors. However, Machine learning methods are considered data-driven and work satisfactorily for long data series and for datasets with similar data specifications. Both models developed in this study are strong enough within the specified data range used in this study and can be used to predict traffic noise for investigating and designing the traffic noise reduction measures in Delhi.

STATEMENTS AND DECLARATIONS

Ethical Approval- The manuscript entitled "**APPLICATION OF M5P MODEL TREE AND ARTIFICIAL NEURAL NETWORKS FOR TRAFFIC NOISE PREDICTION ON HIGHWAYS OF INDIA**". It has not been published elsewhere and that it has not been submitted simultaneously for publication elsewhere further "I have not submitted my manuscript to a preprint server before submitting it to CEER

Consent to participate-

As the study do not involve human subjects, vulnerable group and study do not describe human transplantation study, therefore the consent from participation is not required for this study/ publication.

Funding- Not applicable

Availability of data and materials- Data is collected and analysed personally and it has not been taken from anywhere else.

Ethical responsibilities of authors-

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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