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Research Article

Predicting traffic induced noise using artificial neural network and multiple linear regression approach

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Abstract

Urban noise pollution has risen to the top of the list of issues related to the human health in recent years. Automobiles are the primary source of noise in cities. The noise analysis has been carried out on the busy streets of Ahmedabad, Gujarat's commercial hub and the state's most populous city. This research proposed a model using soft computing approach, artificial neural networks (ANN), for the prediction of environmental urban noise. The ANN technique was applied on the collected data which is chosen streets in an urban region. The outcomes were compared to the multilinear regression model (MLR). According to the study, the ANN system is able to forecast urban noise with better mean square error (MSE) of 5.4 as compared to MSE of 9.30 forecasted by MLR.

Keywords

Noise level, Traffic composition, Artificial neural network, Multilinear regression.

1.Introduction

A sound that degrades one's quality of life is referred to as noise. The noise generated by automobiles is referred to as "community noise." Road, rail, air traffic, industries, construction and public works and the neighbourhood are all major sources of community noise [1]. Many countries have implemented noise regulations by enacting emission guidelines and regulating building acoustics. Due to the lack of techniques to define and measure it, as well as the difficulties of managing it, few countries have restrictions on neighbourhood noise. Communication disruption, sleep disturbance, noise-induced hearing loss, cardiovascular and psychophysiological impacts, and performance decline are the health effects of these exposures [2].

1.1Sound pressure and noise level

Sound levels can be perceived differently by various people, it is required to quantify sound levels in numerical terms. Sound pressure level (SPL) is a term used to describe how loud something is. The SPL is defined as Equation 1.

$$L_p = 10 \log_{10} (P/P_r)^2 \qquad (1)$$

Where L_p = SPL in dB
P = root mean square sound pressure, usually in $\mu N/m^2$
P_r = reference sound pressure

The reference sound pressure (P_r) has an internationally agreed value of 20 $\mu N/m^2$ [3]. Equivalent sound level (Leq)can be obtained from SPL (L), over a time period (T), using Equation 2.

$$Leq = 10 \log_{10}[1/T\int_0^t 10^{\frac{L}{10}} dt] \qquad (2)$$

The *Table 1* shows the noise level standard in India for various types of zones during daytime and night time.

Many countries have implemented noise regulations by enacting emission guidelines and regulating building acoustics. Unlike many other environmental issues, noise pollution continues to worsen, accompanied by an increase in the number of complaints from those who are affected. Most people are exposed to a variety of noise sources, with road traffic noise being the most common. The traffic management work is typically carried out by traffic

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police officers in developing nations such as India, who are constantly exposed to traffic noise. The current research examines the amount of noise in Ahmedabad's most congested streets.

Table 1 Ambient noise standard in India

Area code	Category of area / Zone	Limits in DB(A) LEQ*	
		Day Time	**Night Time**
(A)	Industrial area	75	70
(B)	Commercial area	65	55
(C)	Residential area	55	45
(D)	Silence Zone	50	40

The noise pollution (Regulation & control) rules [4]

Nowadays, everyone is concerned about the environment and its sustainability at both the micro and macro levels. The sustainable development goals adopted by the United Nations (2015) have also considered city sustainability as one of the goals, which focuses on reducing per capita environmental impact of cities and making green and public space more accessible, respectively. This goal is focused on improving the urban living environment. The transportation sector is associated with the development of the city and it also affects environmental issues like air pollution and noise pollution. To provide a green, sustainable and liveable city, noise is an important environmental issue that is under-rated when compared to other environmental issues. This has inspired us to work in the field of urban noise pollution.

The main objectives are as under:

1) To predict traffic induced noise using multiple linear regression (MLR) technique and artificial neural network (ANN) technique.
2) To compare the results obtained from MLR and ANN.

This work has been carried out on the congested streets of Ahmedabad city. For the prediction of noise level, various parameters such as vehicle composition, road width, height of buildings in the surrounding of the road and average speed of vehicles are considered. Here two techniques, i.e., MLR and ANN, have been compared to the prediction of noise level on urban streets. The performance parameters considered in the model are coefficient of correlation R^2 and MSE.

The outline of the paper is as follows. Related work has been explored in section 2. Section 3 explored the methodology in detail. Results have been investigated and discussed in section 4. Discussion of the results is in section 5. Finally, it is concluded in section 6.

2.Literature review

The major factors that affect the noise level in urban area include various conditions such as traffic condition, pavement condition, environment and surrounding conditions. Here are some parameters which may be included by various researchers for the noise modelling. Traffic condition: Vehicular composition, percentage of heavy vehicles, speed, volume, traffic density, occurrence of honking events, peak hours of the day, type of fuel, age of vehicle. Pavement condition: Pavement unevenness, potholes, type of pavement, gradient, road geometry, road width. Surrounding & environmental condition: Type of land use, intersection, presence of signals, building height, green cover. Yang et al. (2020) showed that the level of noise in the city is higher during off-peak hours than during rush hours, owing to quicker speeds and more traffic flow. Land use and the surrounding neighbourhood also influence the overall noise level in the area. There is heterogeneous traffic in developing countries like India, which leads to an increase in noise levels due to mixed traffic, congestion, honking, and a lack of awareness [5]. According to Gilani and Mir (2021) the traffic noise system is composed of the road traffic subsystem, the human subsystem, the environment subsystem, the traffic network subsystem [6]. The type of fuel has a significant impact on noise generation. When compared to conventional fuel, electrified vehicles have the potential to reduce traffic noise. Laib et al. (2018) demonstrated that using electric buses on routes with a high bus share of total traffic, low average travel speeds, and a low percentage of other heavy traffic, particularly at bus stops, has a high potential for noise reduction [7]. There is also a significant impact on the noise level on the price of real estate. Lozhkina et al. (2020) have shown that the price of the apartment on the heavy trafficked road is 10 % less compared to the apartment in quiet area. They also studied that the traffic noise creates an extreme risk of cardiovascular disease among senior citizens (aged over 65) that live in apartments with high noise in surrounding area [8]. For the model development, Rey et al. (2020) considered urban variables such as street location, street geometry, urban land use, road traffic control, and public and private transportation. They discovered that there are very significant correlations between noise levels and the variables [9]. Many researchers throughout the world have utilised various approaches and strategies to anticipate noise levels, such as the parametric approach, the non-parametric approach, and simulation. When regulatory road traffic noise data is partial, incorrect, or missing, it is required to classify and qualify the data by prioritising certain sources of information and criteria above others. Chen et al. (2020) developed a per-vehicle noise prediction model for hilly areas using a multilayer feedforward ANN model. The ANN-based noise prediction model outperformed the empirical predictive equations in terms of accuracy [10]. Using the Morris screening method, Aumond et al. (2021) performed an overall sensitivity analysis of the common noise assessment methods in Europe (CNOSSOS-EU) model [11]. Due to the predictability and precision, soft computing approaches such as fuzzy logic, ANN, adaptive Neuro-fuzzy inference system (ANFIS) and others are becoming more popular in comparison to classic statistical regression techniques. AlKheder et al. (2021) used an ANFIS to predict the traffic noise level on a ringroad in Kuwait, considering different variables such as the noise level in traffic, the number of light and heavy vehicles, road width, average speed, building height, pavement condition, and air temperature and pavement temperature [12]. Gilani et al. (2021) used a graph theory technique to build road traffic noise models that included factors relating to the road traffic subsystem. Vehicle speed, the width of the carriageway, number of heavy vehicle traffic volume, number of heavy trucks, and number of honking incidents were among the road traffic subsystem variables chosen for modelling. The parameterization of traffic noise prediction models varies, and as a result, different estimations of noise levels may be produced based on the geographical context in terms of emission sources and propagation field [6]. Petrovici et al. (2020) applied a multifractal approach to the propagation of acoustic waves. The approach's uniqueness originates from the freedom of the multifractal model, which allows for the simulation of a wide range of acoustic wave behaviours utilising the fractality degree [13]. Thakre et al. (2020) conducted a study on one of Nagpur's minor roads for two years, from 2012 and 2019, using a MLR model that took into account parameters such as traffic volume, honking, and speed versus noise equivalent levels. They found a 5–6 dB(A) increases in noise level and a 65.9% and 81.9 percent increase in sound pressure during morning and evening sessions, respectively, for the years 2012 and 2019 [14]. Chang et al. (2019) monitored 24-hour average road traffic noise levels and analysed the frequency components over the course of a year to develop noise exposure land-use regression models. To create land-use regression models, noise measurements were combined with land-use types, road and traffic statistics, meteorological data, and geographic information systems [15]. In Xu et al. (2022) recorded noise levels over several seasons and developed a LUR model to assess the spatial variability of intra-urban noise and identify potential sources. To create LUR models, noise measurements were combined with land-use types, transportation networks, socioeconomic data, and geographic information systems. The model's performance was evaluated using tenfold cross-validation. LUR can be a reliable strategy for expressing noise variability in megacities where noise maps are not accessible, according to the researchers [16]. Lan et al. (2020) proposed a method for obtaining representative road traffic noise maps of different periods using an urban road traffic noise spatiotemporal distribution mapping method. The proposed noise spatiotemporal distribution model with two time-dependent variables-traffic density and traffic speed - and spatiotemporal features generated from multisource data are used in this method [17] For the period 1995 to 2014, Iglesias-Merchan et al. (2021) modelled the spatiotemporal variations in road traffic noise pollution in an Ecoregion of roughly 66,000 km2. To expand noise modelling across the entire ecoregion, they used MLR. They speculated that noise pollution levels from road traffic may not rise in lockstep throughout wide geographic areas, possibly due to the concentration of big, fast traffic volumes on modern highways connecting cities [18]. Jiménez-Uribe et al. (2020) examined the impact of vehicular traffic on the environmental noise spectrum throughout a 12-km road stretch of Santa Marta's tourism route having five locations in urban and suburban areas. It demonstrated that low frequencies had more energy than high frequencies and were influenced by the time of day, according to the noise spectrum. During the day, all types of vehicles influenced low frequencies, but high frequencies were influenced by both day and night [19]. Using common noise metrics, diverse traffic noise patterns across road networks remain generally undifferentiated. Peng et al. (2021) developed two supplementary noise indicators for road traffic noise to address this issue. The first supplemental indicator distinguishes between the effects of noise exposure during the day and at night. The second supplemental indication distinguishes commuter traffic noise from heavy truck noise. Both indicators are expressed as hourly contributions of light and heavy vehicle noise, as well as typical traffic noise indicators [20]. One of the land uses that are susceptible to road noise is schools. While schools are required to be quiet zones, many are located in metropolitan areas and are subjected to excessive levels of noise. During school hours, Shaaban and Abouzaid (2021) conducted an assessment of traffic noise around different schools in Doha, Qatar. The findings revealed that noise levels are positively connected with traffic volume near the schools, implying that areas with larger traffic volumes have higher noise levels [21]. The influential variables and their contribution to the generated noise level at signalised T-intersections, cross-intersections, and roundabouts were determined using regression modelling by Khajehvand et al. (2021) the findings revealed that the total traffic volume, as well as the number of cars, pavement condition index, and speed, have a substantial impact on noise levels. Furthermore, traffic noise levels are higher at roundabout exit approaches than at roundabout entrance approaches. Furthermore, unforeseen events and non-lane-based behaviour resulted in a dramatic increase in the maximum sound level as departure approaches [22]. Asensio et al. (2021) proposed a method of computation that allows us to isolate the contribution of a specific vehicle to overall noise pollution in an urban setting, and they used the CNOSSOS-EU framework as a base for compatibility with the European noise mapping plan [23]. For the CBD of Ondo, Nigeria, Ibili et al. (2022) investigated traffic noise levels and produced models. Traffic noise models for the measurement of equivalent noise levels (Leq) at the CBD of Ondo were developed using the empirical methods of the calculation of road traffic noise (CoRTN) model and statistical MLR modelling methodology. With acceptable coefficients of determination (R2) values of 0.943 and 0.963, respectively, the correlation between CoRTN and MLR models demonstrated reliable efficiency relative to observed noise levels, indicating that the method is robust and accurate in estimating the level of noise from road traffic for the study area [24]. Reidel et al. (2021) investigated the sensitivity of older citizens to road traffic noise. They studied 1691 people aged 60 to 90 years old who filled up questionnaires about their exposure to road traffic noise (Lden) at the most exposed façade. A path model with linear regressions on engagement-specific self-efficacy and communal mastery measures and probit regressions on binary planned and performed engagement variables was used to test the assumed relationships. The findings revealed a few group-specific vulnerabilities, such as the link between engagement-specific self-efficacy and performed an engagement among participants living in higher-social-welfare neighbourhoods who were also exposed to greater levels of exposure [25]. In Port Harcourt, Nigeria, Ihemeje et al. (2021) presented a state-of-the-art review on the assessment and modelling of traffic noise intensity on roadside inhabitants. They looked at a variety of strategies and proposals for reducing the noise intensity for the health of people living near traffic lanes that had been recommended in earlier studies [26]. On an original dataset gathered in Patiala, India, Singh et al. (2022) developed a machine learning-based prediction of SPL. Data on vehicular traffic and SPL was collected at several locations throughout the city. The obtained data is augmented to ten times its original size using Monte Carlo simulation, and ANN for vehicular traffic noise prediction are trained and compared to other Machine learning approaches [27]. De et al. (2017) created an adaptive traffic noise model for a noise-prone zone's susceptible society. To assess the risk of noise, they devised a fuzzy logic system. They took into account the normality and non-normality of participation for various noise parameters, such as noise intensity, exposure period, and the impacted age group of people in a specific location, and graphical depictions were created for the model's overall rationale [28]. Ranpise et al. (2021) measured ambient noise levels along key arterial roads in Surat, compared them to mandated criteria, and developed a noise prediction model for arterial roads based on an ANN with a feed-forward back propagation method for training [29]. Machine learning (ML) modelling approaches were utilised by Ali et al. (2019) to accurately estimate roadway traffic noise. Regression decision trees, support vector machines, ensembles and ANN were among the machine learning approaches used. A conventional regression model produced earlier under the same conditions was compared to the best developed ML model. The cross-validated results show that the best machine learning model surpassed regression modelling [30]. Gundogdu et al. (2005) created two prediction models based on genetic algorithms (GA) that can be used to restructure the traffic flow within cities. Some of the noise data was used to validate the models [31]. Szwarc and Czyżewski (2011) used a GA to describe an innovative method of noise prediction for the railway [32]. Rao and Tripathy (2019) investigated the noise produced in bauxite mines by various noise sources. They used MATLAB to test the applicability of a genetic method. They came to the conclusion that GA can converge faster and discover the best values in a reasonable amount of time [33]. The sound quality of each operation condition and position of the tractor was evaluated using the rating scale approach by Chen et al. (2022) the authors developed a back propagation neural network (BPNN) and a support vector regression (SVR) model, which were then improved using a GA. The GA was found to increase the model's prediction accuracy and greatly minimise the severe errors when the experimental findings were verified [34]. Debnath et al. (2022) investigated noise descriptors for contour plotting and discovered the suitability of ANN for the prediction of traffic noise in the Dhanbad township, concluding that the ANN approach is far superior to any other statistical method in predicting the traffic noise level [35]. In general, urban noise mapping entails modelling noise emission and attenuation in a given area Lesieur et al. (2019) used radial basis functions as interpolators in their meta modelling for urban noise mapping. Noise Modelling, an open-source software, was used to create the meta-model. The meta-model simulations are almost 10,000 times faster than the model while keeping the core characteristics [36]. To investigate traffic noise at roundabouts and signalised intersections, Li et al. (2017) employed a traffic noise simulation method based on microscopic traffic simulation. An experimental method was used to develop a vehicle noise emission model that takes into account the influence of acceleration. Traffic noise around roundabouts and signalised intersections was simulated at various traffic volume levels [37]. The following *Table 2* shows the inference of the literature review.

Table 2 Inference of literature review

Approach	**Description**	**Work done by**	**Parameters/ Attributes**
Statistical/Empirical /Regression	With a set of dependent and independent variables, it is a parametric technique. It is straightforward and simple to comprehend. It is not applicable to a complex problem.	Yang et al. (2020) [5]	Traffic volume, speed, land use type
		Gozalo et al. (2020) [9]	street location, street geometry, urban land use, road traffic control, and public and private transportation
		Thakre et al. (2020) [14]	traffic volume, honking, and speed
		Chang et al. (2019) (LUR) [15]	land-use types, road and traffic information, meteorological data
		Xu et al. (2022) (LUR) [16]	land-use types, road networks, socioeconomic variables
Graph Theory	It investigates how networks can be encoded and their attributes determined. Insufficiently suitable to large-scale data	Gilani et al. (2021) [6]	Traffic volume, speed, Street width, Number of heavy vehicles
ANN	In a machine learning prediction model, it's the most useful. When dealing with complex problems with unclear functional relationships, this tool comes in handy. It's a black box that's difficult to decipher.	Chen et al. (2020) [10]	Hilly terrain, gradient, Traffic volume
		Ranpise et al. (2021) [29]	Traffic volume. traffic composition,
		Ali et al. (2019) [30]	Distance, Light vehicle volume, heavy vehicle volume, average speed, roadway temperature
		Debnath et al.(2022) [35]	Traffic volume, percent of heavy vehicles, Speed, traffic flow, road gradient, pavement, road side carriageway distance
Adopted Neuro Fuzzy interface system	These systems can handle a variety of inputs, including data that is ambiguous, skewed, or inaccurate. When the situation is unknown and hazy, this is a good tool to have the inference inherent in human thinking and the processing of imperfect data Human reasoning is used to create rules.	Al Kheder et al. (2021) [12]	traffic noise level, light and heavy vehicle count, average speed of both, road width, building height, pavement condition, and air and roadway temperature
		De et al. (2017) [28]	Age of people, exposure time, noise level and noise risk index as an output.
Genetic Algorithm	The genetic algorithm is a heuristic for searching that is based on Charles Darwin's theory of natural evolution. This	Chen et al.(2022) [34]	Tractor noise and various operations to run tractor including the SPL, A-weighted SPL, loudness, sharpness, roughness, and fluctuation strength

Approach	Description	Work done by	Parameters/ Attributes
	algorithm is modelled after natural selection, in which the fittest individuals are chosen for reproduction in order to produce the children of the next generation.	Rao at al.(2019) [33]	engine noise, exhaust noise, transmission, tyre–road interaction, aerodynamics, body and road rattle
Software & Simulation	Simulation can be used to evaluate the performance of an existing system or to predict the performance of a future system by comparing different solutions and designs. It is possible to study a variety of situations and results.	Lesieur et al (2020) [36]	Traffic topography, meteorological data using noise modeling software
		Singh et al. (2022) [27]	Monte Carlo simulation, traffic composition
		Li et al. (2017) [37]	Light vehicle, medium vehicle, heavy vehicle, their acceleration using microscopic traffic simulation

In the field of noise analysis and prediction modelling, various researchers have carried out work using various techniques and parameters. Some of the techniques require large data while some techniques require less data. So based on the availability of the data the techniques have been chosen. Though now a days many soft commuting techniques are becoming popular, the importance of statistical techniques cannot be ignored. In the developed country, the traffic is homogeneous while in developing country like India, there is heterogeneous traffic. There is no proper lane change behaviour in India. There is no enforcement to reduce honking on urban streets. So the work done in developing country may not get fit in the condition of Indian streets. In case of highway or freeway, the factors affecting noise are different from the factors affecting noise level in urban areas.

3.Methodology

In this study, the noise level data have been collected in the study area. The variables affecting noise level have been collected through traffic volume count survey (i.e., traffic composition and flow), spot speed survey (i.e., speed of vehicle) and road inventory survey (i.e., road width, building height). The collected data have been analysed and noise level prediction has been carried out using MLR and ANN. *Figure 1* shows the methodology chart of the study work. After finalizing the study area, the data collection is carried out. There are two types of data collected i.e., primary data and secondary data. Primary data collected manually while secondary data have been obtained from various open sources. Data have been initially analysed using MS excel. Then, using SPSS software and MATLAB software the prediction model is developed. At the end conclusion and discussion is carried out. *Figure 1* shows the methodology adopted to conduct the research work.

3.1 Study Area

The current research is conducted in Ahmedabad, India, along a major traffic route. Ahmedabad is India's seventh largest metropolis, with a geographical area of approximately 464 km2 and a road network of approximately 2600 km. The population, which was around 5.58 million in 2011, is expected to reach around 8 million by 2022. *Figure 2* shows the population growth in Ahmedabad. The same way the density of traffic is increasing day by day. The city has 26 lakh vehicles, with a growth rate of 2.19 lakh vehicles each year. In the recent two decades, the city has seen tremendous expansion in the number of automobiles, with about 49 lakh registered vehicles as of March 31, 2020, with more than 70% being two-wheelers. *Figure 3* shows the vehicular growth in Ahmedabad. Stadium crossroad to Thaltej cross Road, a 6.2-kilometre-long traffic corridor, has been chosen for data collection. *Figure 3* shows the locations of data collection. This corridor is flanked by property uses such as commercial and residential. Because of the barricades put along the stretch owing to metro rail work, the corridor is partially closed at various locations and thus the lane width (LW) varies in the study area. For simplicity of data collection, the entire corridor has been divided into seven links. *Table 3* shows the link details such as link name, its available lane width, the average building height. The link 1 (stadium to commerce crossroad) is a four-lane divided sub arterial road and the rest of the links are six lane divided arterial road.

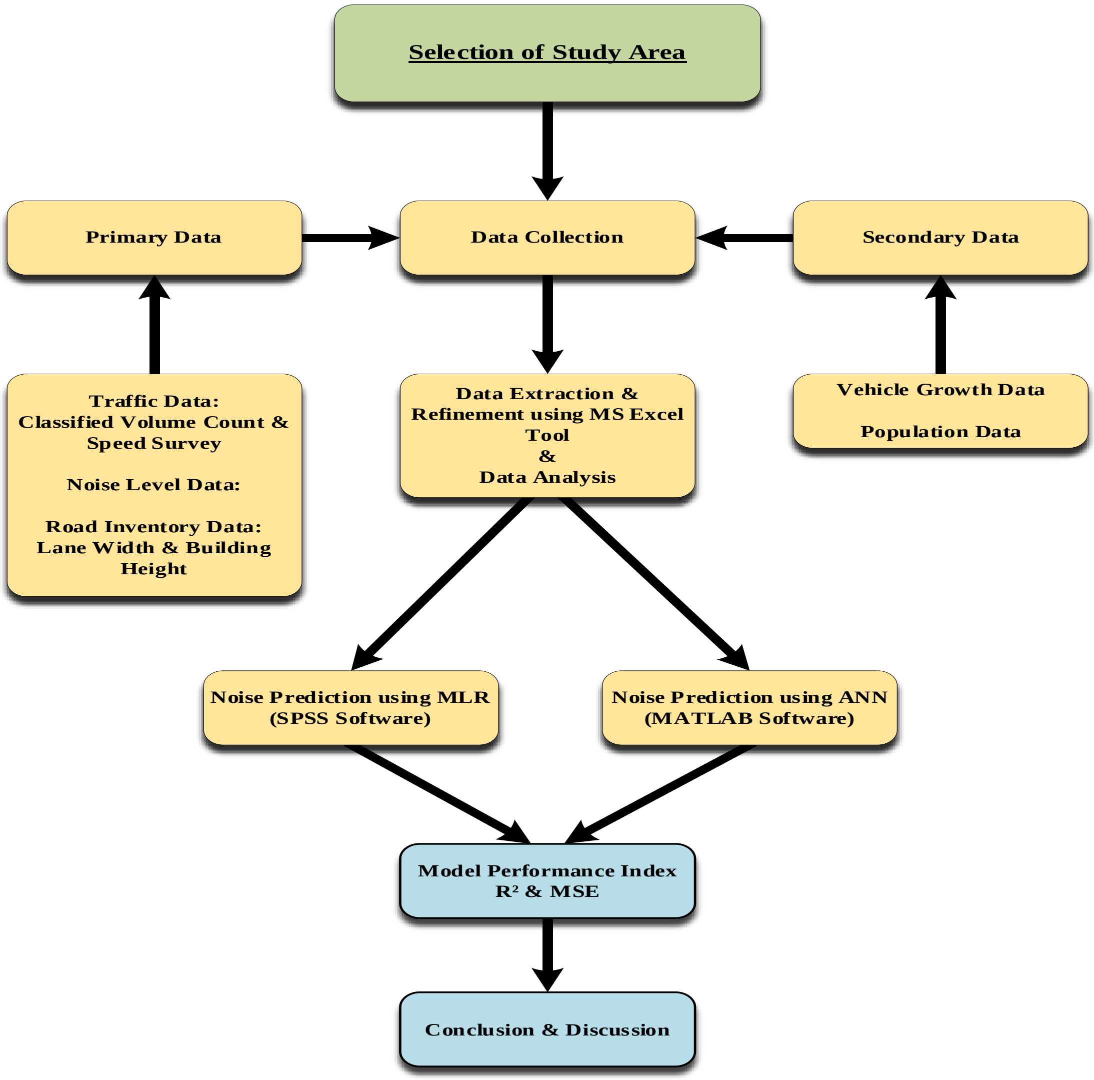

Figure 1 Methodology chart

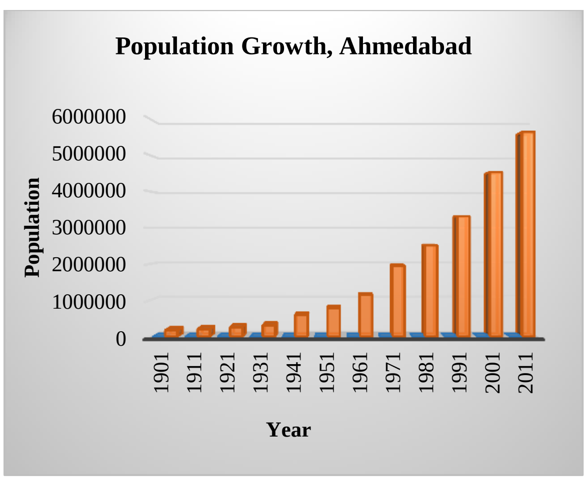

Figure 2 Population growth in Ahmedabad

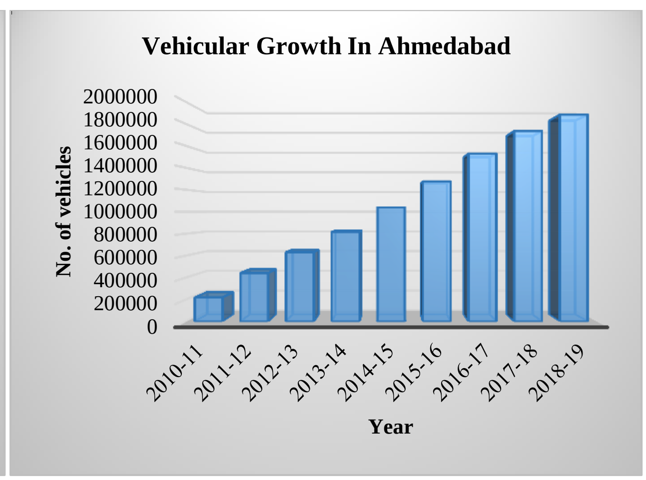

Figure 3 Vehicular growth in Ahmedabad

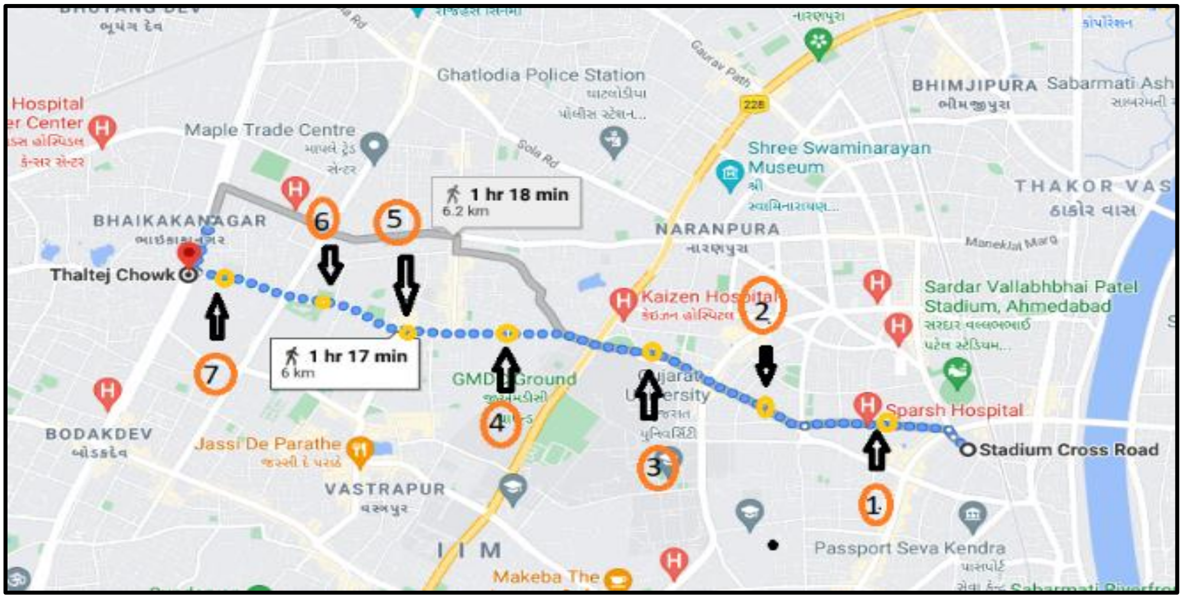

Figure 4 Study Area (Google map)

Table 3 Study area description

Link No.	Link name	Lane width (M)	AVG. Building height (M)
1	Stadium crossroad to Commerce crossroad	3.6	7.95
2	Commerce crossroad to Vijay crossroad	5.2	7.56
3	Vijay crossroad to Helmet crossroad	6.5	4.54
4	Helmet crossroad to Gurukul crossroad	4.4	12.83
5	Gurukul crossroad to Sunrise Park crossroad	9	7.53
6	Sunrise Park crossroad to Sal crossroad	3.8	7.04
7	Sal crossroad to Thaltej crossroad	6	5.4

3.1Data collection

The data have been collected in the month of April 2019 during weekdays. Automobiles are major sources of noise in urban areas. So, the data have been collected during the morning and evening peak hours of the day. To consider the off-peak noise level, the data have been collected during noon hours as well. Data have been collected for every 5-minute interval in the morning from 9:00 a.m. to 12:00 noon, at midday from 1:00 p.m. to 3:00 p.m. and in the evening from 6:00 p.m. to 9:00 p.m. The time selected for the data collection is based on the rush hour of the day. The morning and evening peak hour and afternoon off peak hours have been selected for the data collection. The data have been collected on the 7 locations of the study area.

3.2.1 Noise data collection

A sound level metre (SL-4001) is used to measure the noise level. It was positioned at a height of 1.5 metres above the ground. Because the available lane width of all stretches is not the same, the distance between the road's centre line and the noise level metre varies. At every 5 min interval noise level has been recorded along with the traffic data.

3.2.2 Traffic data collection

The classified volume count survey is carried on each location using videography method during morning, noon and evening hours. For every 5 min interval, the total number of vehicles passing through the section is counted. The vehicle composition is obtained from the data extraction i.e., number of two-wheelers (TW), car, three-wheeler (3W), light commercial vehicle (LCV) and Bus. Again, a spot speed survey is conducted to collect the speed data of the vehicles.

3.2.3 Road inventory

The road inventory data have been collected during early morning 5.30 am to avoid conflicts with the traffic. The length and width of the road are measured using an odometer (a portable handy measuring wheel). The building height is measured by considering 1 floor height is 3.0 m and also verified it with a 30 m tape. *Table 4* shows the sample data sheet in which time of data collection, noise level, traffic composition, total volume and average speed are mentioned.

Table 4 Sample data set

Sr. No.	Time	Level of noise in dB(A)	2W	3W	Car	LCV	Bus	Vehicles /5min	Speed (km/h)
1	9.00-9.05 am	97.00	71	12	16	0	0	99	27.33
2	9.05-9.10 am	96.90	77	13	12	0	1	103	30.37
3	9.10-9.15 am	97.20	70	12	17	1	4	104	34.13
4	9.15-9.20 am	97.30	75	16	13	0	1	105	30.44
5	9.20-9.25 am	97.60	75	14	16	3	0	108	32.27
6	9.25-9.30 am	100.10	91	20	16	19	2	129	33.48
7	9.30-9.35 am	97.20	68	17	19	1	4	109	31.80
8	9.35-9.40 am	98.50	85	17	19	0	0	121	36.59
..	..	..	..	..	..	..	..	..	..
672	8.55-9.00 pm	104.9	73	21	37	19	2	152	18.80

4.Result and data analysis

The study area is near busy roadways with hospitals, business centres, apartments, temples etc. As a result, there isn't much of a difference in noise levels in the morning, noon, and evening period. From the *Table 5*, it is observed that the maximum flow is on the link number 6 (Sunrise Park to Sal crossroad) and minimum flow is observed on link no.3 (Vijay to Helmet). The maximum Speed is observed on link number 2 and minimum speed is observed on link no.5. Here it is important to note that link no. 4, 5 & 6 are surrounded by shops, complexes, multiplex & cinema, hospitals, restaurants, government offices, public library, high rise apartments etc. So here the average flow is high and the observed speed is less as compared to another link.

Table 5 Speed, Flow &Density on each Link

Link No.	Link name	Average flow (Vehicle / 5min)	Average speed (km/h)	Density (No of Vehicle/km) *
1	Stadium to Commerce	98	22.55	52
2	Commerce to Vijay	126	30.86	49
3	Vijay to Helmet	66	25.93	31
4	Helmet to Gurukul	131	19.43	81
5	Gurukul to Sunrise Park	132	19.28	82
6	Sunrise Park to Sal	136	19.63	84
7	Sal to Thaltej	64	24.7	31

$$\text{*Density} = \frac{Flow(no\ of\ veh./\ km)}{Speed\ (km/hr)} \qquad (3)$$

Density is not measured from the survey. Density is derived from the Equation 3 as the ratio of flow to the speed. Density is a function of flow and speed.

Figure 4 shows the maximum, minimum L_{10}, L_{50} and L_{90} noise level in the study area. L10 is the level that exceeds 10% of the time. The sound or noise has a SPL exceeding L_{10} for 10% of the time. L_{10} is frequently utilized in traffic noise assessments and planning applications. L_{50} is the level that exceeds 50% of the time. It's the statistical middle of the noise measurements. L_{90} is the level that exceeds 90% of the time. The noise level is usually above this level, 90% of the time. It is commonly thought to indicate the noise environment's background or ambient level (*Figure 5*).

The maximum noise is observed in Sal to Thaltej link and Gurukul to Sunrise Park link having value having 110.8 dB (A) and 110.6 dB (A) respectively. As it is commercial area there is not much variation between the noise level. All the locations have maximum value greater than 100 dB(A) which is very high as compared to the Indian standard of noise level. The same way the minimum noise level is observed on Sunrise to Sal crossroad link which id 80 dB(A) again higher than the standard value.

After data collection, initially the data have been analyzed using MS excel. *Table 6* Shows the descriptive statistics of the variables in which range, minimum, maximum, mean, standard error and standard deviations are mentioned. To understand the relationship among the variables, correlation matrix plays an important role. By using MS excel the correlation matrix is prepared. *Table 7* shows the correlation amongst the variables. The variables i.e., two-wheeler, three-wheeler and Cars are in good correlation with Leq. The speed is negatively associated with the noise level. The building height and lane width are not in good correlation with noise level.

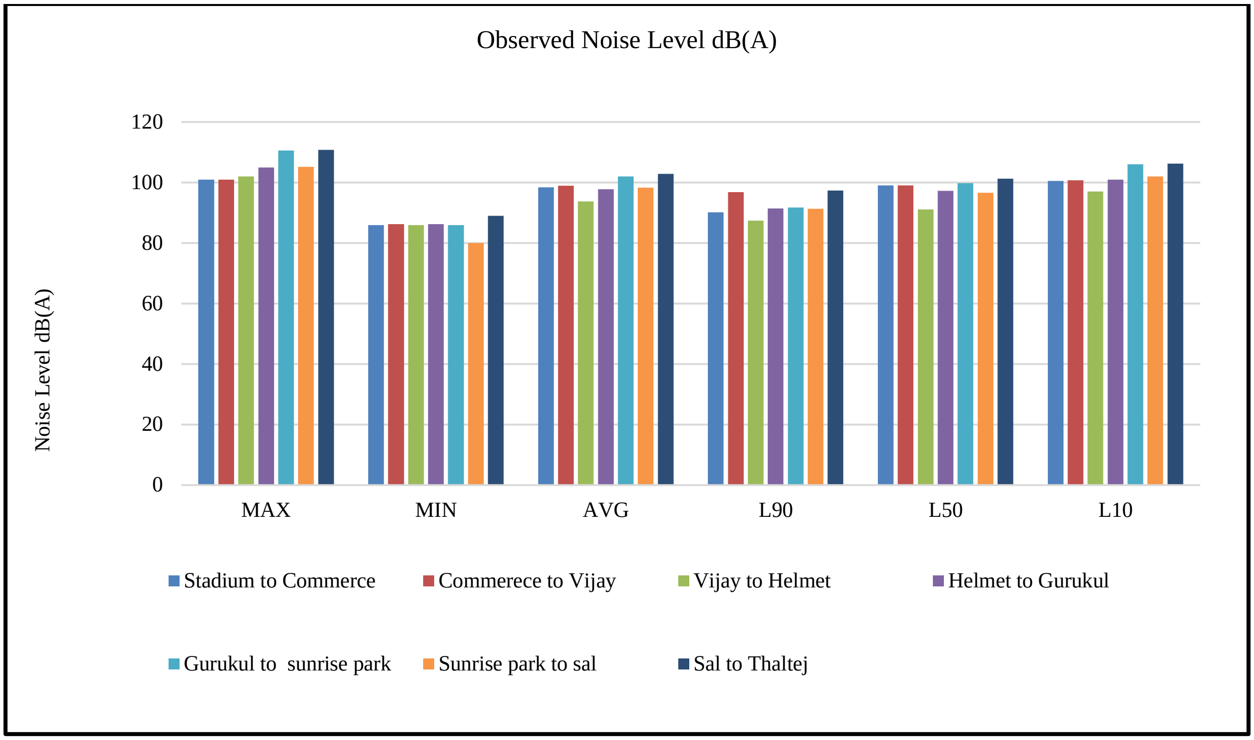

Figure 5 Noise level in study area

Table 6 Descriptive statistics

	Range	**Min.**	**Max.**	**Mean standard error**	**Standard deviation**
Leq	30.8	80	110.8	0.21	4.95
2W	106	22	128	0.81	19.20
3W	28	5	33	0.24	5.66
Car	47	4	51	0.35	8.41
LCV	19	0	19	0.11	2.59
Bus	4	0	4	0.05	1.10
SP	25.67	12.25	37.92	0.27	6.52
LW	5.5	3.5	9	0.08	1.81
BH	8.47	4.36	12.83	0.10	2.42

Table 7 Correlation matrix

	Leq	**2W**	**3W**	**Car**	**LCV**	**Bus**	**SP**	**LW**	**BH**
Leq	1								
2W	0.7	1							
3W	0.47	0.48	1						
Car	0.57	0.41	0.48	1					
LCV	0.36	0.13	0.2	0.41	1				
Bus	0.21	0.07	0.25	0.33	-0	1			
SP	-0.1	0.09	-0	-0.1	-0.3	0.2	1		
LW	0.07	-0.1	-0	0.24	0.26	0.06	-0.2	1	
BH	0.09	0.25	0.1	-0.1	-0.1	-0.1	0.11	-0.3	1

4.1Statistical technique: MLR

One of the most extensively used statistical approaches is regression analysis. A multivariate statistical technique for examining the relationship between a single dependent variable and a group of independent variables is known as MLR analysis. The goal of MLR analysis is to predict a single dependent variable using independent variables whose values are known. The following equation expresses the effect of independent factors on response as Equation 4.

Where Y is dependent variable, b_0, b_1, b_2,..b_n are estimated regression coefficients for linear relation and X_1, X_2 ....X_n are independent variables.

The MLR has been carried out using SPSS software. The parameters considered for the regression analysis are equivalent noise level (Leq) as dependent variables and 3W, 2W, car, LCV, Bus, average speed of vehicles in kmph, average building height (BH) on the street and LW. *Table 8* shows the MLR model summary. The R^2 value is coming out 0.624. So it is concluded that the relationship among the variables are moderate.

Table 8 MLR summary model-1(8 Input variables)

Model summary	
R	0.790
R Square	0.624
Adjusted R Square	0.618
Standard Error of the Estimate	3.05594

Predictors: (Constant), Vehicle Speed, Two-Wheeler, Bus, Lane Width, LCV,
Three-wheeler, Building Height, Car

The performance of the multilinear regression is checked by the ANOVA test. *Table 9* shows the results of ANOVA test. The value of mean square of error is coming out as 9.339.Here at the confidence interval 95 %, the significant f value is coming out 0.00 which is less than 0.05.So as a whole by considering R^2 value and f significant value, the prediction model performs well (*Figure 6*).

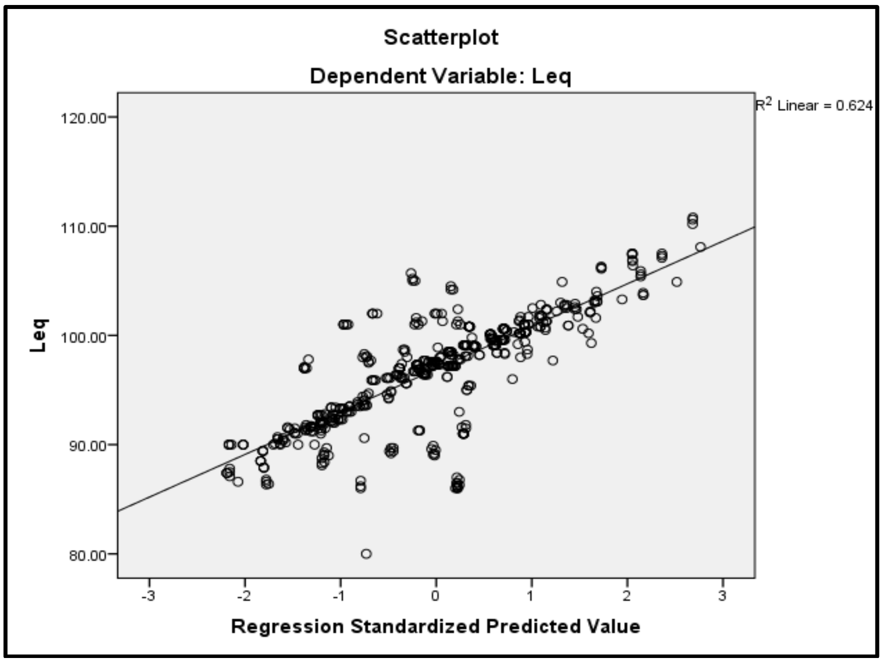

Figure 6 Scatter plot (Observed vs. Predicted)

Table 9 ANOVA test model-1

Model	Sum of square	DF	Mean square	Statistical F test value (f)	Significance value (Sig.)
Regression	8633.911	8	1079.23	115.6	0.00
Residual	5211.045	558	9.339		
Total	13844.956	566			

The model is formed as equation-4 by considering 8 input variables.

$$\boldsymbol{Leq} = 84.227 + 0.148*2W + 0.028*3W + 0.112*car + 0.358*LCV + 0.515*Bus - 0.057*SP - 0.014*LW + 0.018\,BH \quad (4)$$

It is necessary to investigate the influence of each input variable on output. *Table 10* shows the coefficients and t values of each variable. Here the data are two directional. For two tailed test, t critical value at 556 degree of freedom (df) is 1.962. By comparing the t calculated values with t critical, it is observed that the variables i.e., 3W, LW and BH do not have significant impact on noise prediction. *Table 10* shows coefficients and t statistics of the data.

Table 10 Coefficients (Model-1)

Const.	Unstandardized coefficients		Stand. Coeff.	t	Sig.
	B	Std. Error	Beta		
	84.22	0.986		85.385	0.000
2W	0.148	0.008	0.576	17.664	0.000
3W	0.028	0.028	0.032	0.980	0.328
Car	0.112	0.021	0.191	5.309	0.000
LCV	0.358	0.057	0.188	6.236	0.000
Bus	0.515	0.132	0.115	3.906	0.000
SP	-0.057	0.022	-0.075	-2.617	0.009
LW	-0.014	0.078	-0.005	-0.183	0.855
BH	0.018	0.058	0.009	0.306	0.760

By considering the outputs obtained from correlation matrix (*Table 7*) and t statistics (*Table 10*), the variables i.e. LCV, bus, SP, LW & BH have been removed and once again the regression process is carried out. *Table 11* shows MLR summary for model-2. The parameters considered for the regression analysis are equivalent noise level (Leq) as dependent variables and 3W, 2W, car. *Table 11* shows the MLR model summary for model-2. *Figure 7* shows the scatter plot of observed vs predicted noise level. The R^2 value is coming out 0.716. So it is concluded that the relationship among the variables are moderate.

Table 11 MLR summary model-2 (3 input variables)

Model summary	
R	0.846
R Square	0.716
Adjusted R Square	0.710
Std. Error of the Estimate	2.8113

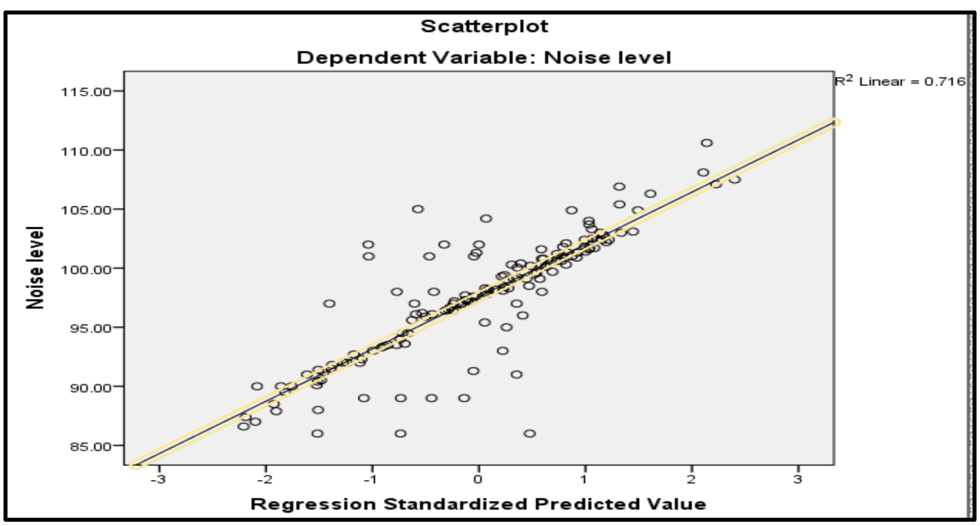

Figure 7 Scatter plot (observed vs predicted)

The performance of the multilinear regression is checked by the ANOVA test. *Table 12* shows the results of ANOVA test. The value of mean square of error is coming out as 10.25. Here at the confidence interval 95 %, the significant f value is coming out 0.00 which is less than 0.05. So as a whole by considering R^2value and f significant value, the prediction model performs well.

Table 12 ANOVA test model-2

Model	Sum of square	DF	Mean square	f	Sig.
Regression	8073.5	3	2691.7	262.52	0.00
Residual	5771.4	563	10.251		
Total	13844.9	566			

Table 13 shows the coefficients of the variables. The model is formed as Equation 5 by considering 3 input variables.

Leq *= 81.926 + 0.149*2W + 0.104*3W + 0.174*car* (5)

To investigate the influence of these three input variables on output, it is required to check t value. *Table 13* shows the coefficients and t values of each variable. Here t critical value of 563 degrees of freedom for 95% of confidence intervals is 1.962. By comparing the t calculated values with t critical, it is observed that all three variables t-calculated value is greater that t critical value. So, it is concluded that there is a significant influence of these variables on noise level.

Table 13 Coefficients model-2

Consttant	Unstandardized coefficients		Standard coefficient	t	Sig.
	B	Std. Error	Beta		
	81.926	0.886		92.428	0.000
2W	0.149	0.013	0.574	11.052	0.00
3W	0.104	0.047	0.118	2.228	0.027
Car	0.174	0.028	0.329	6.330	0.00

4.2Artificial neural network

The data have also been analysed using ANN. The neural structure of the brain is used to create artificial neural network models. ANN, like the brain, learn from their experiences. ANNs have been proved in previous studies to be suitable for pattern recognition and classification applications due to their nonlinear nonparametric adaptive-learning capabilities. ANN is now commonly used in analysing business data stored in databases or data warehouses as a useful analytical tool. Network training is an important phase in neural network application. ANNs are widely employed in a variety of engineering and science fields, and their unique ability to approximate complex and nonlinear equations makes them a useful tool in quantitative research. The capacity of neural networks to represent both linear and non-linear interactions is its fundamental strength and benefit. The data have been analysed by ANN using MATLAB 2020 software. Following figure shows the ANN architecture.

Process to train network

Theinput variables have been fed to the network. The network algorithm considered for the network in TRAINLM- Levenberg Marquardt. This algorithm requires more memory and less time. The training automatically stops when generalization stops improving as indicated by increase in mean square error (MSE) of validation sample. The supervised learning approach has been used as it predicts the output. The function approximation used is multilayer perceptron (MLP).It consists of one input layer and several hidden layers based on the complexity of the problem. *Figure 8* shows the ANN architecture.

Training for 8 input variables

Here same as MLR, equivalent noise level (Leq) as output variable and 3W, 2W, car, LCV, Bus, average speed (SP) of vehicles , average building height (BH) on the street, LW have been considered as inputs. From the total data, 70 % data have been used for training of the network while 15 % data have been used for testing the network and 15 % data have been used for the validation of network. The transfer functions used for hidden layer and output layers are tan-sig and purelin respectively. *Figure 9* shows the ANN architecture in MATLAB having one input layer with 8 input variable, 10 hidden layers and one output layer. After training data, the performance parameter i.e., mean squarer error (MSE) is coming out 4.934 after 28 iterations which is shown in *Figure 10*. *Figure 11* shows the error histogram. The error concentration in the range of -2 to +2 and the error for training, testing and validation is following normal distribution.

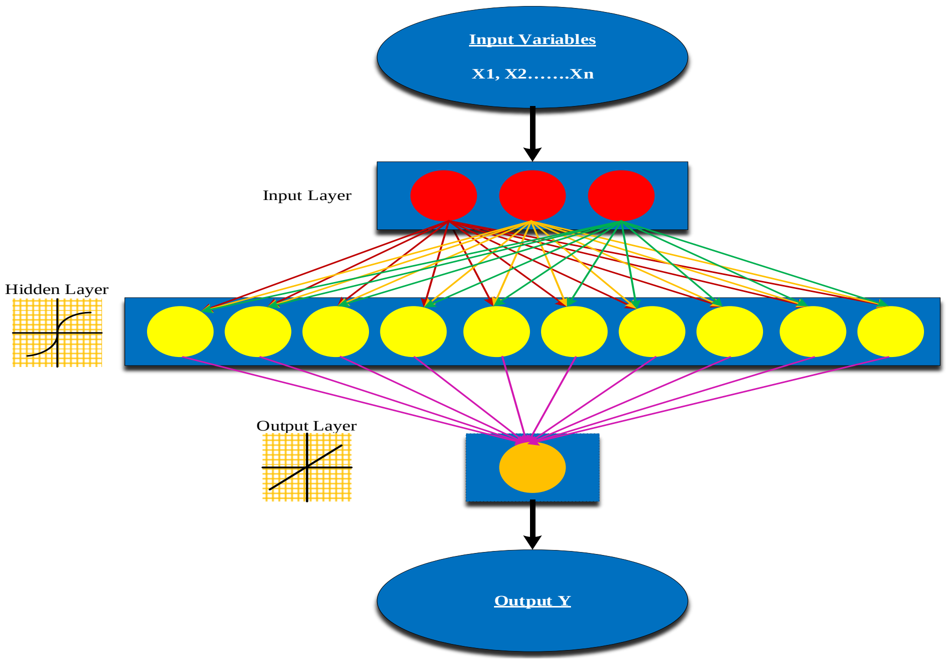

Figure 8 ANN architecture

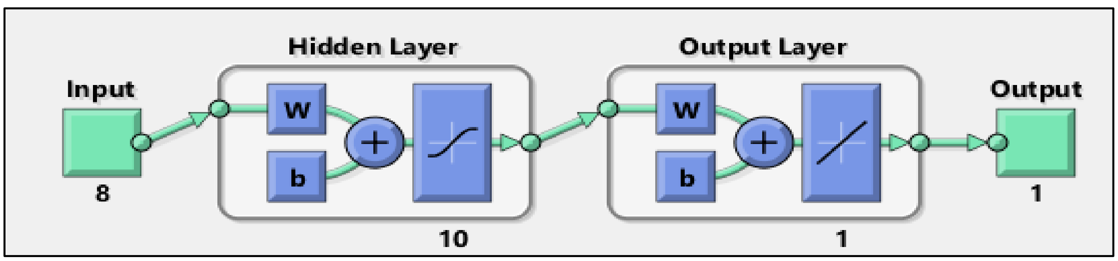

Figure 9 Network in MATLAB for 8 input variables

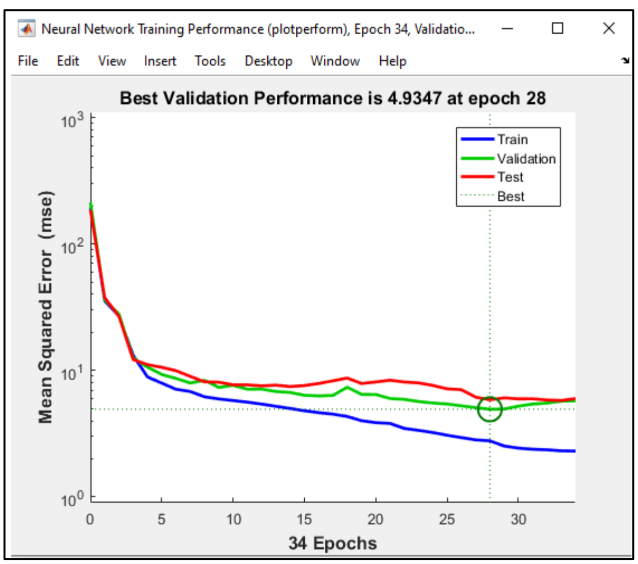

Figure 10 Performance of network (MSE)

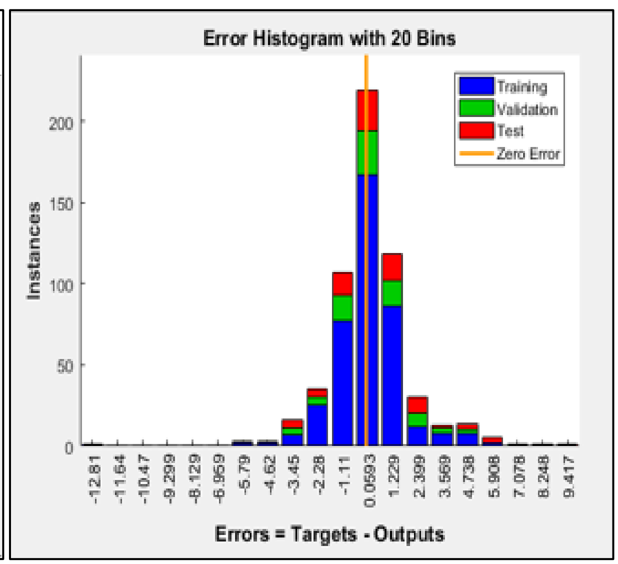

Figure 11 Error histogram

Figure 12 shows scatterplot of target vs output data. The R values for training, validation and testing are 0.942, 0.903 and 0.861 respectively. The overall R value is 0.924 and R^2value is coming out as 0.855.

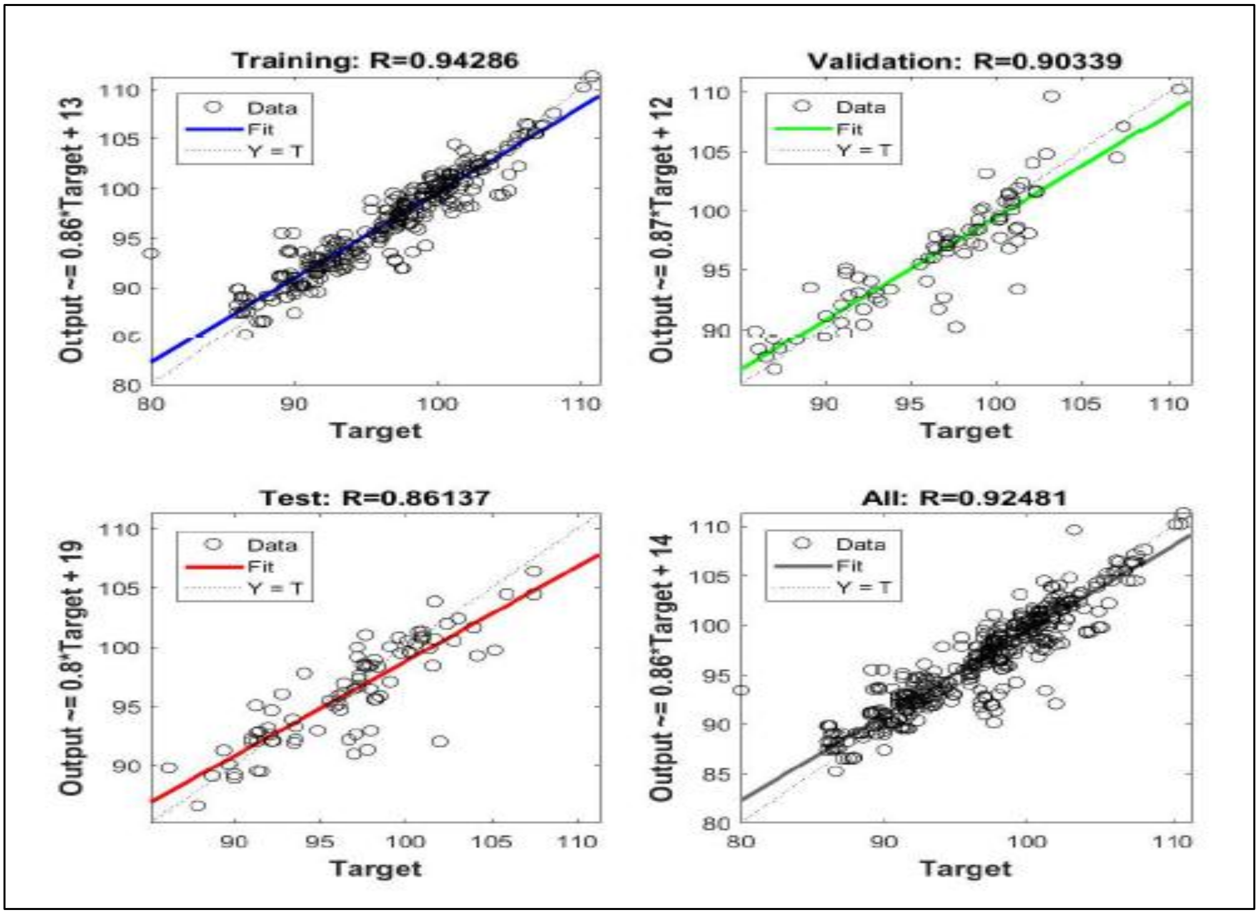

Figure 12 Scatter plot target vs output (Leq)for training, testing, validation. (For 8 input variables)

Training for 3 input variables

Equivalent noise level (Leq) as output variable and three wheeler (3W), two wheeler (2W), car have been considered as input variables.70% of the data was used for network training, 15% for network testing, and 15% for network validation. Tan-sig and pure line are the transfer functions used for the hidden and output layers, respectively. In MATLAB, *Figure 13* depicts an ANN design with one input layer, three independent variables, ten hidden layers, and one output layer.

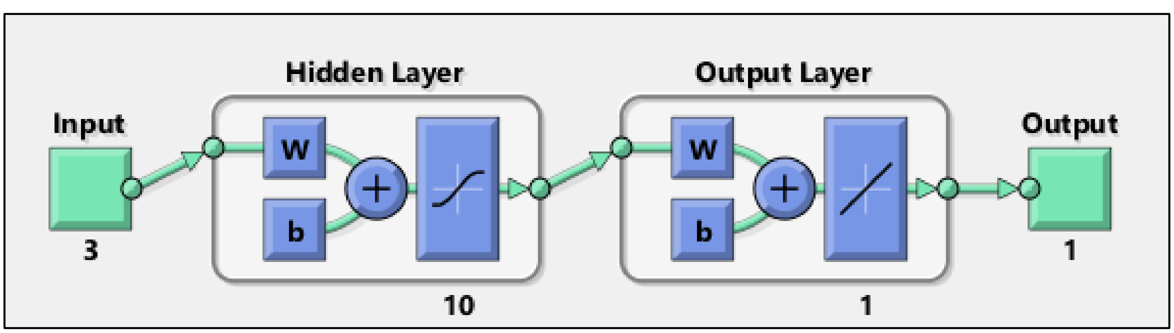

Figure 13 Network in MATLAB for 3 input variables

After training data, the performance parameter i.e., mean squarer error (MSE) is coming out 5.4197 after 35 iterations which is shown in *Figure 14*. *Figure 15* shows the error histogram. The error concentration in the range of -3 to +2 and the error for training, testing and validation is following normal distribution.

Figure 16 shows scatterplot of target vs output data. The R values for training, validation and testing are 0.962, 0.880 and 0.839 respectively. The overall R value is 0.862 and R2 value is coming out as 0.791.

By considering both the results obtained from ANN and MLR, it is observed that using MLR technique the R2 value of model -1 is coming out as 0624 having MSE value as 9.339. By using ANN technique, the R2 value is coming out as 0855 and MSE value is 4.934. After reducing the number of input variables, for model-2 MLR gives R2 value as 0.716 and MSE value as 9.30. ANN technique gives better value of R2 as 0.791 and MSE as 5.4 as shown in *Table 14.*

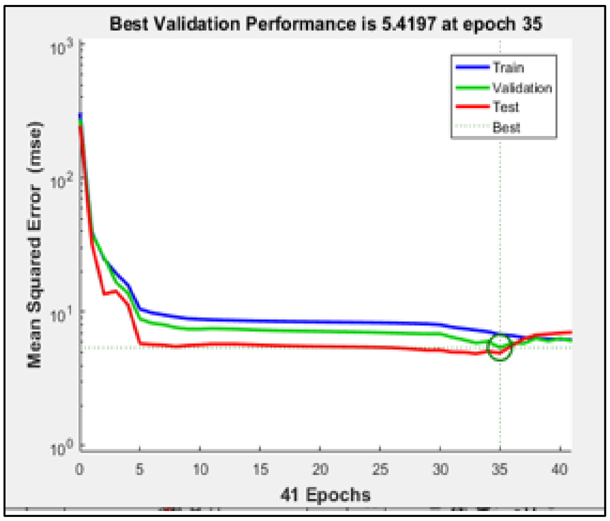

Figure 14 Performance of network (MSE)

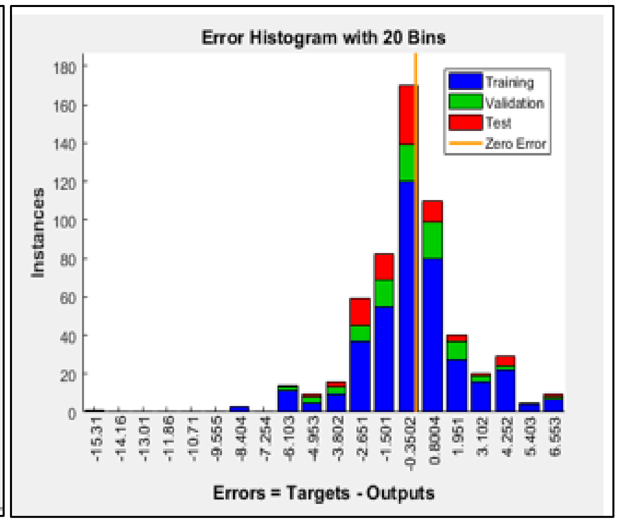

Figure 15 Error histogram

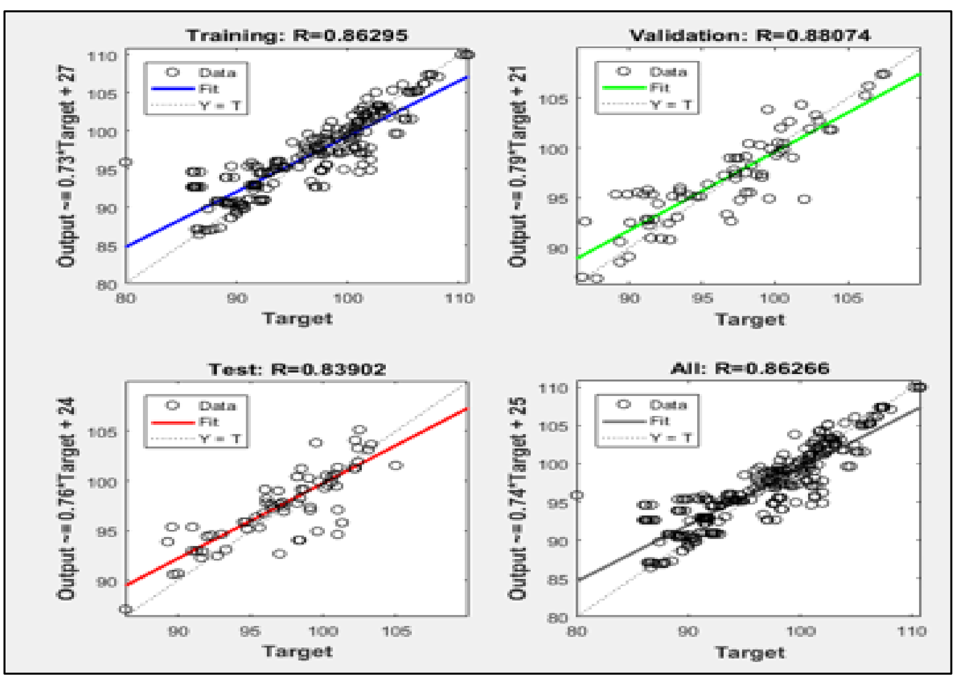

Figure 16 Scatter plot target vs output (Leq) for training, testing, validation

Table 14 Comparison of results of MLR and ANN

Technique	Model/Network	No. of input variables	R^2 Value	MSE
MLR	1	8	0.624	9.339
MLR	2	3	0.716	9.30
ANN	1	8	0.855	4.934
ANN	2	3	0.791	5.4

5.Discussion

Key Findings

- The factors considered for the prediction of noise are traffic composition (i.e., two-wheeler, three wheeler, car, light commercial vehicle, bus), average speed of vehicles, LW, building height.
- The maximum average traffic flow (vehicle/5min) is observed on the link no.-6 (Sunrise Park to Sal crossroad) which is 136 vehicles/5 min. The maximum speed is observed on link no.-2 (Commerce crossroad to Vijay Crossroad) which is 30.86 kmph. The observed noise level ranges from 80 dB to 110 dB throughout the corridor.
- The collinearity matrix shows that two-wheeler has strong collinearity with Leq followed by car, three-wheeler and LCV.
- From the study, it is observed that LW, speed of vehicles does not have a significant impact on noise levels. This may be due to the heavy trafficked conditions. Many times, there was a forced flow condition in the study area.
- In the study area, the major composition of traffic is two-wheeler followed by car and auto rickshaws. From the correlation analysis, it was proved that the major affecting parameters are the same.
- Generally, heavier vehicles have high noise emission as compared to lighter vehicles. But in the study area the proportion of heavy vehicles is very less.
- First regression analysis has been carried out for 8 variables i.e., model 1. From the regression analysis, it is observed that the factors i.e., two-wheeler, three-wheeler, Car have positive coefficients. The average vehicle speed, building height and LW are the factors which are negatively associated with the noise level. i.e., as speed increases the noise level decreases. The R^2 value for multilinear regression is 0.624 and mean square error is 9.339. From the ANOVA test, it is observed that the predictability of MLR model is fair having significant f value is nearly zero which is less than 0.05.
- But some of input variables i.e., 2W, 3W and car have t values within in the limit means t observed is greater than t critical. But the rest of the variables do not fall in the acceptable limit of t critical value. So, the rest of the variables are removed and once again the regression is carried out for three variables i.e., model 2. This time t value and p value fall in the acceptable limit.
- From the comparison point of view the network has been trained by considering 8 input variables and 3 input variables.
- For ANN, TRAINLM- Levenberg Marquardt algorithm is used. There are 10 hidden layers. The data used for training, validation and testing are 70%, 15% and 15% respectively.
- For network 1, the overall R^2 value for 0.855 and mean square error is 4.934. For network-2 the overall R^2 value for 0.791 and mean square error is 5.4.

Implication:

- The corridor is surrounded by commercial and residential area. The corridor width is reduced due to the barricades installed because of metro rail construction work. The observed noise level is very high as compared to the standard value. The continuous exposure to the people in the nearby area is also very high. This would be a reason for various health problems.
- The noise level in the study area is much higher than the standard value. The health of the people who work in that area, as well as the residents, is in grave jeopardy.
- The noise prediction will be useful to the researchers for further work. It will also be useful to the policy makers to take mitigation measures in affected domain.

Limitations: This work is limited to the city having heterogeneous traffic and also limited to the techniques i.e., MLR and ANN. Some variables such as pavement condition and occurrence of honking event are not included. A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion and future scope

In this article, two modelling techniques are used: neural network and statistical technique. The capacity of these models to forecast is determined by the mean square error and R2. We discovered that in forecasting, neural networks outperform statistical techniques. The multilinear regression model has an R2 value of 0.624 and 0.716 for 8 input variables and 3 input variables respectively, whereas the ANN has a better prediction value and a lower MSE value. The noise level in the study is much higher than the standard.

Future Scope: There are some factors that might be considered during the modelling of the noise predictions such as pavement conditions, gradient, honking event etc. The area of neural networks is quite diverse, and there are numerous avenues for future research, including data pre-processing, representation, application, architecture selection and so on.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
Toral Vyas and H. R. Varia: Study conception and design, Analysis and interpretation of results, contribution to the paper as follows, reviewed the results and approved the final version of the manuscript.

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Appendix I

S. No.	Abbreviation	Description
1	2W	Two-Wheeler
2	3W	Three-Wheeler
3	ANFIS	Adaptive-Network-based Fuzzy Inference System
4	ANN	Artificial Neural Network
5	Auto	Auto Rickshaw
6	BH	Building Height
7	BPNN	Back Propagation Neural Network
8	CBD	Central Business District
9	CNOSSOS-EU	Common Noise Assessment Methods in Europe
10	CoRTN	Calculation of Road Traffic Noise
11	DF	Degree of Freedom
12	f	Statistical F Test Value
13	GA	Genetic Algorithm
14	HV	Heavy Vehicles
15	Leq	Equivalent Continuous Sound Level
16	LCV	Light Commercial Vehicle
17	LUR	Land Use Regression
18	LW	Lane Width
19	MLP	Multilayer Perceptron
20	MLR	Multiple Linear Regression
21	MSE	Mean Square Error
22	SP	Speed
23	SVR	Support Vector Regression
24	Sig.	Significance Value
25	TRAINLM	Training Algorithm Levenberg Marquardt