# Assessment of Traffic Induced Noise in Dhaka Using an Artificial Neural Network Approach

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**Abstract.** In Dhaka, urbanization is growing at a rapid rate which has brought about an increase in road traffic, resulting in a significant rise in noise pollution levels. This study aims to assess the relationship among various vehicle types and the noise generated by these vehicles. Study locations were set near educational institutions and hospitals as these are noise sensitive areas. To assess the noise pollution levels, data were collected at several locations throughout the week. The average $L_{eq}$ in the morning and afternoon hours were found to be higher than the standard level of 60dB set by the Department of Environment in Bangladesh, indicating the severity of the noise pollution problem. For further analysis, a multilayer feed forward artificial neural network model was developed which was trained using Bayesian Regularization (BR) algorithm. The model was used to predict $L_{eq}$ and $L_{10}$ in dB and used hourly volume data of different vehicle types, including heavy, medium, light, and non-motorized vehicles as well as road width as input variables. The regression value obtained from the model indicated a moderate correlation (R=0.75) between the inputs and outputs. From further analysis light vehicles were found to be the biggest contributor of noise pollution in these areas.

**Keywords:** *artificial neural network, noise pollution, vehicle-noise correlation.*

## 1 Introduction

Noise pollution refers to the presence of unwanted or excessive sounds that have the potential to cause detrimental effects on human well-being, wildlife, and the overall quality of the environment. The study area Dhaka is one of the most densely populated cities worldwide, where noise pollution is escalating with other forms of pollution as population continues to expand. Traffic is the principal source of noise in Dhaka city, among many other sources like industries, construction works, use of loud speaker etc (Chowdhury et al. 2010). The cumulative impact of traffic-related noise can have far-reaching consequences. For every 5-decibel rise in the average 24-hour noise level the risk of heart attacks and strokes is increased by 34% (European Heart Journal,2019). Noise can potentially cause disorders in immune system and inhibit sleep (Prasher,


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2009). When children are exposed to noise over an extended period of time and repeatedly, it might affect their psychological health as well as their drive to learn (Buchari et al. 2017).

Traffic noise is dependent on characteristics of the vehicle flow, interaction of tires with road surface, traffic flow conditions, and driving habits (Subramani et al., 2012.). Subramani et al. (2012) developed a mathematical model for predicting $L_{eq}$ by considering parameters like volume of vehicle, average speed, surface temperature, and humidity. In another study by Thakre et al. (2020), a traffic noise prediction model was created for an Indian road. The study showed that with a 95.4% increase in traffic volume from 2012 to 2019, $L_{eq}$ increased by 4.4 dB(A). Additionally, a study by Wen et al. (2019) observed that schools near expressways faced more noise pollution than those located beside arterial roads and branch roads. The research also concluded that classrooms with open windows were exposed to more noise.

Use of machine learning in noise pollution prediction can bring successful results. A study by Hamad et al. (2017) used artificial neural network (ANN) model to predict equivalent noise based on variables like traffic volume, roadway temperature, average speed and distance from the edge of the road. The model yielded great results with a $R^2$-value 0.996. The study also found distance from the edge of the road and light vehicle volume to be the two most important variables. Another study used multilayer feed forward Levenberg–Marquardt algorithm to develop a model to predict $L_{eq}$ and $L_{10}$ as outputs. The model used traffic volume, heavy vehicle percentage and vehicle speed as input parameters. The study also found neural network model performed better than regression model as it had high correlation coefficient and less error (Kumar et al., 2014). Another study also found that ANN model ($R^2$= 0.82) performs better than ridge regression model ($R^2$= 0.67) while correlating noise and traffic (Chowdhury V et al., 2021).

Based on previous researches, this study used artificial neural network model to assess correlation between traffic parameters and noise metrics. Traffic parameters such as different types of vehicle volume and road width were used as input variables. Equivalent noise level($L_{eq}$) and $L_{10}$ are the outputs of the model. The research focused on areas near educational and healthcare institutions in Dhaka, as limited research currently exists for this specific category of facilities in the city. Furthermore, assessing the contribution of vehicles in noise generation is significant for proposing future mitigation measures.

## 2 Methodology

### 2.1 Study Location

Five locations within Dhaka were selected for data collection. These locations included two hospitals and three educational institutions. The locations are:

**Table 1.** Locations of sampling points

| | Location | Abbreviation |
|---|---|---|
| Educational Institution | Engineering University Girls' School and College | E1 |
| | University Laboratory School and College | E2 |
| | Udayan Uchcha Madhyamik Bidyalaya | E3 |
| Hospital | Sheikh Hasina National Institute of Burn & Plastic Surgery | H1 |
| | Government Employee Hospital | H2 |

## 2.2 Data Collection

For this study, noise was measured at five locations in morning and afternoon for a week. 7am to 12pm was designated as morning, and 12pm to 5pm as afternoon. At each sampling station, noise was collected for 2 minutes using a noise meter. The meter was calibrated beforehand. Slow response time and 'A' frequency weighting were chosen during the data collection process.

Simultaneously, two-way uninterrupted traffic volume was recorded for 15 minutes, which was then extrapolated to find hourly traffic volume. The video footage was thoroughly examined to calculate traffic volume and categorize vehicle types. Vehicles were divided into 4 different classes: heavy, medium, light and non-motorized vehicle (NMV). Field observation found that light vehicles were the most in number and bus, trucks were not that prevalent. However, this observation might vary in different study location.

**Table 2.** Vehicle Categorization

| | |
|---|---|
| Heavy Vehicle | Bus, Truck |
| Medium Vehicle | Private car, Microbus |
| Light Vehicle | Motorcycle, Auto-rickshaw |
| Non-motorized Vehicle | Rickshaw, Bicycle |

## 2.3 Calculation of $L_{eq}$ and $L_{10}$

After collecting data, equivalent noise level ($L_{eq}$) and $L_{10}$ were calculated. $L_{eq}$ is the continuous steady sound level that would have the same total acoustic energy as the fluctuating noise measured over the same period of time. the following equation is used to calculate equivalent noise level:

$$L_{eq} = 10\, log_{10}\, [\frac{1}{n} \sum_{i=1}^{n} f * antilog\, \left(\frac{Li}{10}\right)]$$

Where, Li = instantaneous noise level; n = number of samples in the sampling period; f = frequency of each range. The median value of each range from cumulative frequency distribution curve was taken as Li (Hassan & Alam, 2013).

$L_{10}$ denotes the noise level exceeded for 10% of the time. $L_{10}$ is often used to evaluate traffic noise since it accounts for any irritating noise peaks.

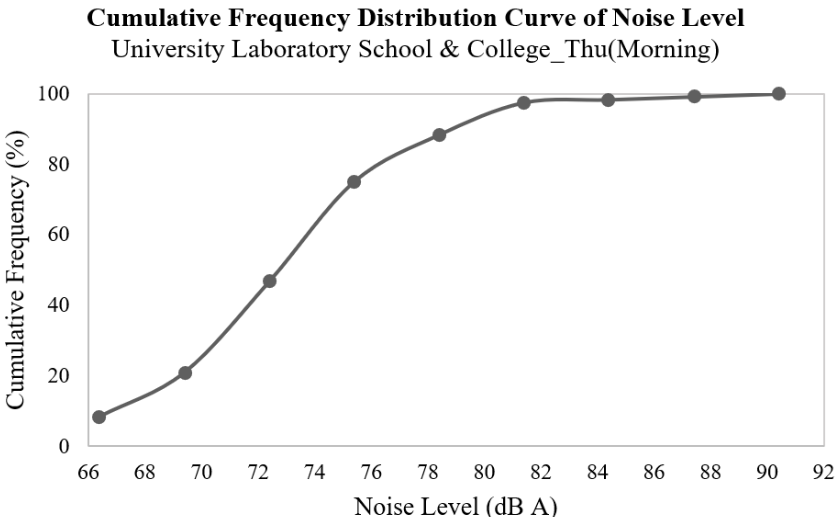


**Fig. 1.** Cumulative Frequency Distribution Curve of Noise Level (E2 Thursday Morning)

## 2.4 Model Development

In this study, the neural net fitting tool in MATLAB was used to construct a multilayer feed forward neural network model that was trained using the Bayesian Regularization (BR) training algorithm. The Bayesian Regularization (BR) training algorithm is more equipped to deal with smaller and noisier datasets (Chowdhury V. et al. 2021).

In this study, 5 input variables were used, namely: hourly volume of heavy vehicles (HV), hourly volume of medium vehicles (MV), hourly volume of light vehicles (LV), hourly volume of non-motorized vehicles (NMV) and road width (RW). Equivalent noise level (Leq) and L10 was in the output layer. There was a single hidden layer with 7 neurons. Through trial and error, the number of hidden layers and neurons were determined.

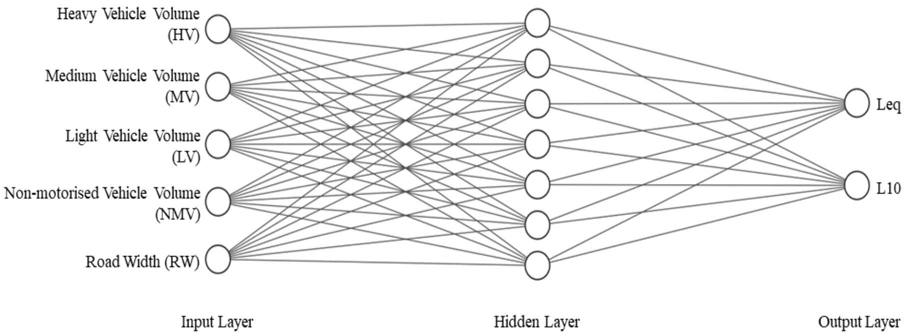


**Fig. 2.** Architecture of neural network model

The dataset was divided into two subsets, a model development set containing 60 observations and an evaluation set containing 10 observations. The model development set was further divided into training dataset (85%) and testing dataset (15%). Train and test data ratio was selected by trial and error. The model that produced the best result was selected. After preparing the model its' performance was checked using the evaluation dataset.

# 3 Results and discussion

## 3.1 Variation of Noise Level Throughout the Week

In the majority of situations, the study revealed that weekdays were noisier than weekends. It should be noted that in Bangladesh, Friday and Saturday are typically considered weekends.

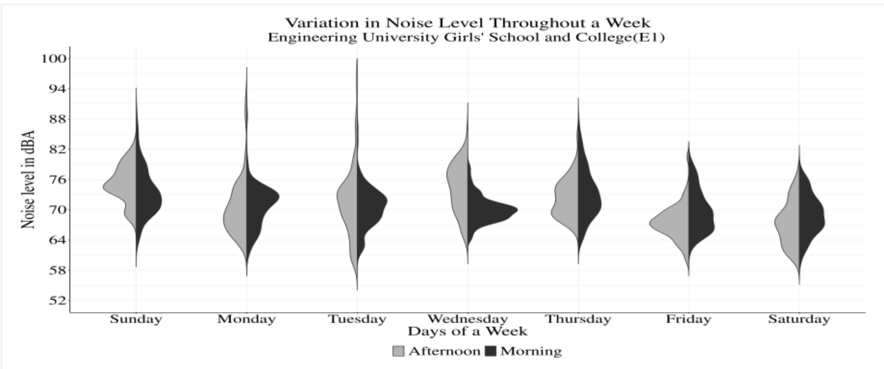


**Fig. 3.** Variation in Noise Level at Location E1

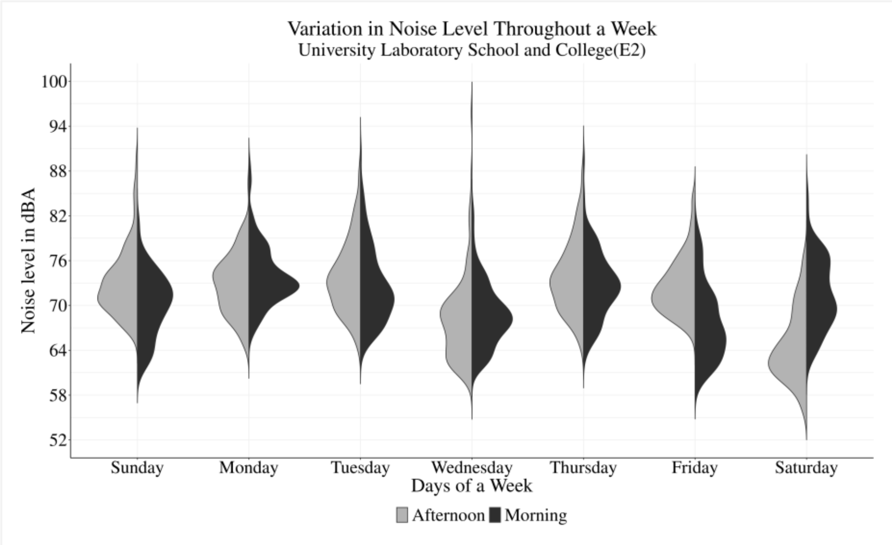


**Fig. 4.** Variation in Noise Level at Location E2

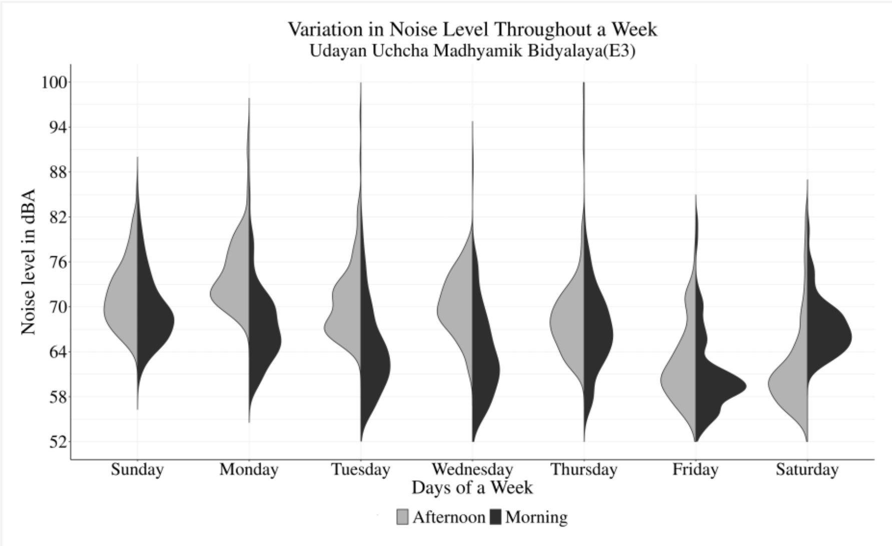


**Fig. 5.** Variation in Noise Level at Location E3

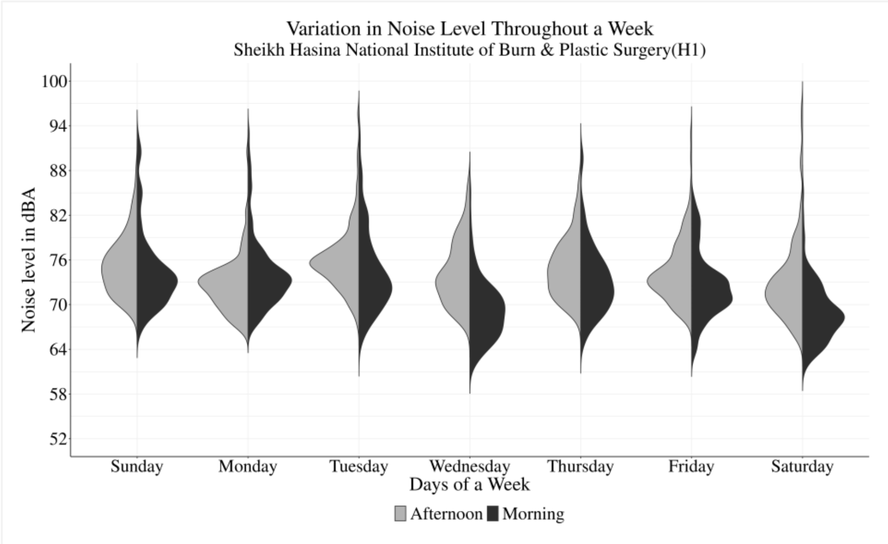


**Fig. 6.** Variation in Noise Level at Location H1

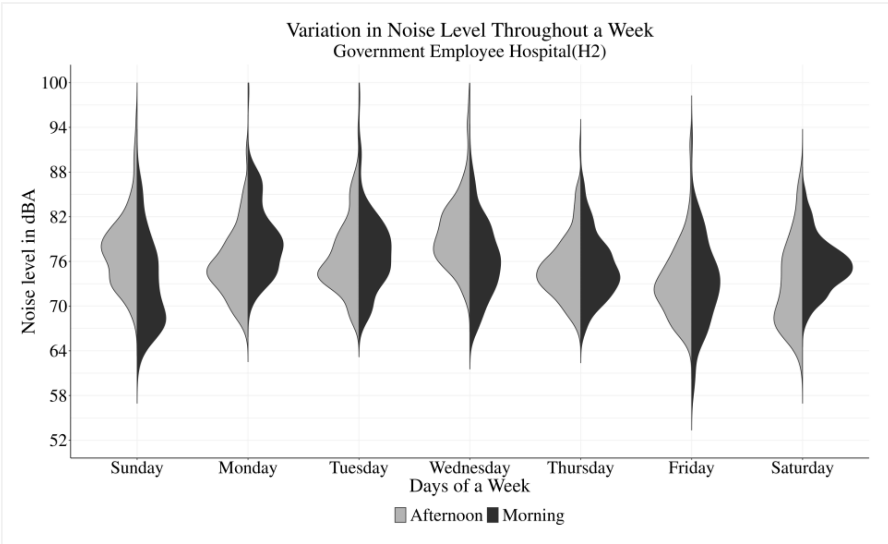


**Fig. 7.** Variation in Noise Level at Location H2

Fig. 3 to 7 show the variation in noise level throughout the week using violin plots. For example, location E3 in Fig. 5 is more likely to experience noise in the range of 60 dB to 74 dB during the weekday mornings. This location is also exposed to the least amount of noise on Friday where the lowest value was about 53 dBA. The reason for this could be that, since it is a school that is closed on weekends, the amount of traffic generated noise naturally decreases. Also, vehicle counts showed that the total number of vehicles on that road decreased on weekends, resulting in less noise. Some outliers can also be identified from the graph. Based on field observations, these outliers occurred when a vehicle drove very close to the noise meter or by the use of loud horns. Overall, hospital adjacent roads were found to be noisier throughout a week.

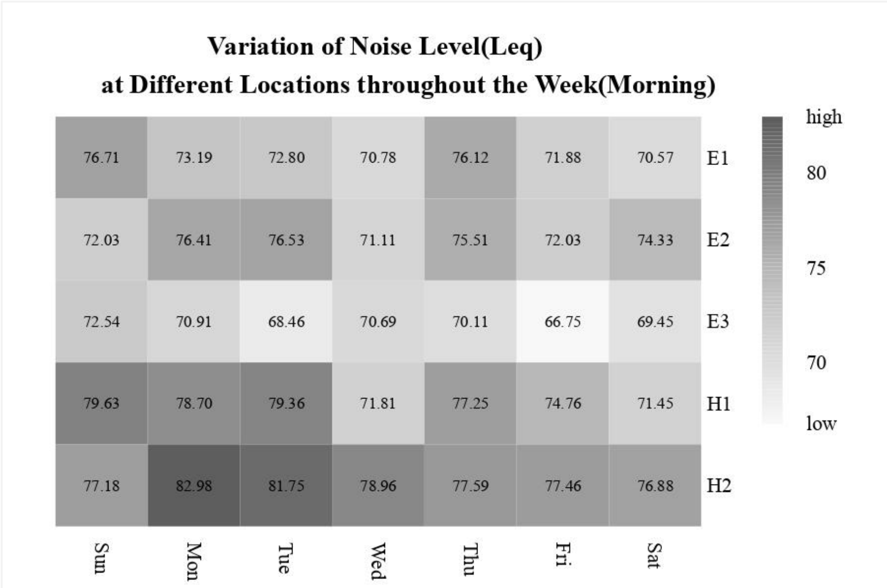


**Fig. 8.** Weekly Variation of $L_{eq}$ (Morning)

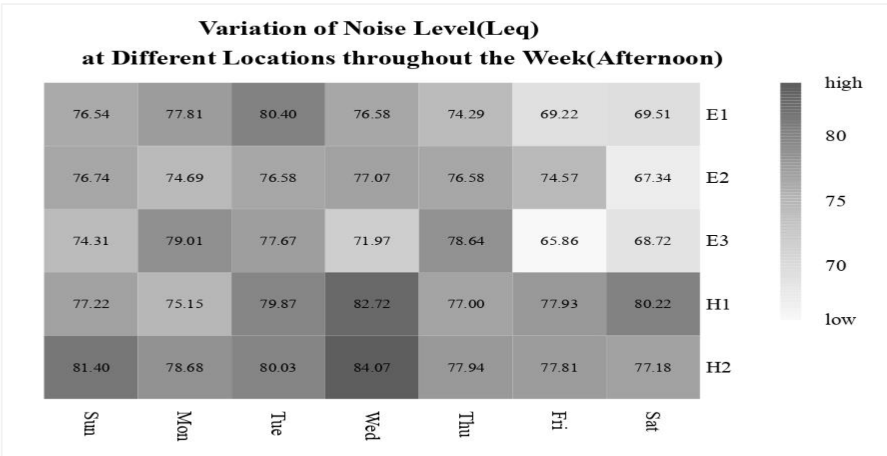


**Fig. 9.** Weekly Variation of $L_{eq}$ (Afternoon)

From Fig. 8 and 9, it can be seen that $L_{eq}$ appeared to be the lowest in front of Udayan Uchcha Madhyamik Bidyalaya (E3) and the highest in front of Government Employee Hospital (H2). The minimum and maximum equivalent noise level in morning were 67 dBA and 83 dBA respectively. Similarly, the minimum and maximum equivalent noise level in afternoon were 66 dBA and 84 dBA respectively.

The reason for $L_{eq}$ variation is dependent on the surrounding environment of the sampling points. Udayan Uchcha Madhyamik Bidyalaya is situated on the road which has residential buildings, student halls and other educational institutions on both sides. The road is devoid of any noisy establishments. For which it appears to be the quietest. On the other hand, Government Employee Hospital is situated on a busy main road and features a U-turn just in front of the hospital entrance leading to congestion and a lot of traffic near the location. By comparing morning and afternoon heat maps, it was observed that the afternoons were noisier. The reason for this is due to the location of sampling points. The University Laboratory School(E2) and College, as well as the Udayan Uchcha Madhyamik Bidyala(E3), are located close to the busy Nilkhet signal, which is a bustling market hub. In the afternoon and evening, people tend to gather in this area, leading to an increase in the noise level during those times. Overall, the noise level was found to be over the 60 dBA standard set by the Environment Conservation Rule (1997) of Bangladesh.

### 3.2 Artificial Neural Network Model

For determining correlation between traffic parameters and noise level, an artificial neural network model was prepared using MATLABs' neural net fitting tool. The model included 5 input variables and two output variables. The number of neurons in a single hidden layer were set by trial and error.

**Table 3.** Performance results for one hidden layer ANN models

| #Neurons | Training | Testing | All | |
|---|---|---|---|---|
| | R | R | R | MSE |
| i = 5; h = 7; o = 2 | 0.75291 | 0.72328 | 0.74792 | 0.0837 |
| i = 5; h = 8; o = 2 | 0.7923 | 0.73728 | 0.77123 | 0.0775 |
| i = 5; h = 9; o = 2 | 0.78536 | 0.69537 | 0.7674 | 0.0779 |

The models yielded similar results. The model with 7 hidden neurons resulted correlation coefficient of training, testing and all data as 0.75291, 0.72328 and 0.74792 respectively. The MSE for this model is 0.0837. The correlation among input variables and outputs can be interpreted as moderate.

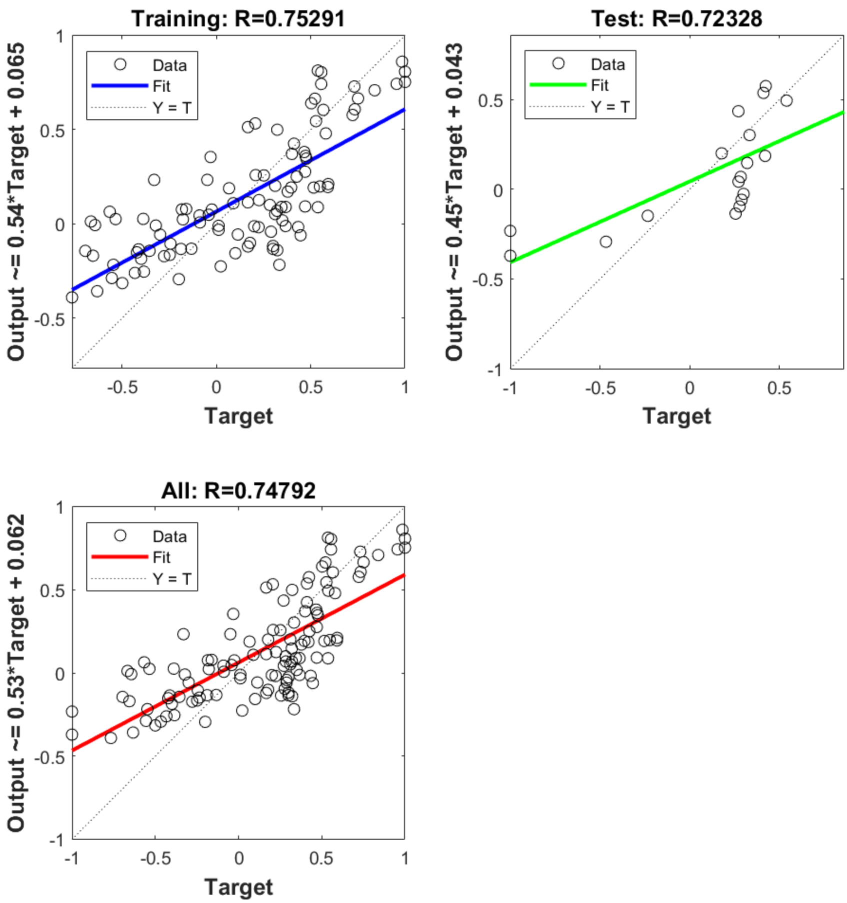


**Fig. 10.** Performance of ANN Model

## 3.3 Model Evaluation

Afterward the model was evaluated using the evaluation set. The R2 value was found to be 0.85 for Leq and 0.81 for $L_{10}$. It means that the model was about to generalize approximately 85% of the variations in the evaluation set for Leq and similarly 81% of the variations for $L_{10}$.

**Table 4.** Comparison between observed and predicted outputs

| Observed $L_{eq}$ (dBA) | Predicted $L_{eq}$ (dBA) | $R^2$ | Observed $L_{10}$ (dBA) | Predicted $L_{10}$ (dBA) | $R^2$ |
|---|---|---|---|---|---|
| 71.79 | 73.10 | 0.85 | 75 | 76.21 | 0.81 |
| 74.29 | 73.04 | | 77.1 | 76.22 | |
| 73.72 | 72.68 | | 75.8 | 76.21 | |
| 74.90 | 74.97 | | 79 | 77.98 | |
| 78.96 | 79.24 | | 82.5 | 83.20 | |
| 77.18 | 78.05 | | 79.3 | 81.95 | |
| 71.11 | 73.39 | | 74.2 | 77.32 | |
| 72.03 | 73.42 | | 75.4 | 77.43 | |
| 72.54 | 72.29 | | 75.9 | 75.67 | |
| 69.45 | 70.03 | | 72 | 73.98 | |

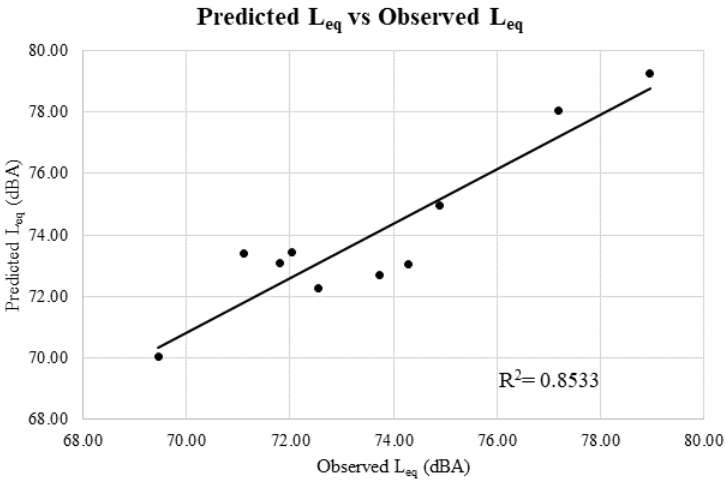


**Fig. 11.** Predicted Leq vs Observed Leq

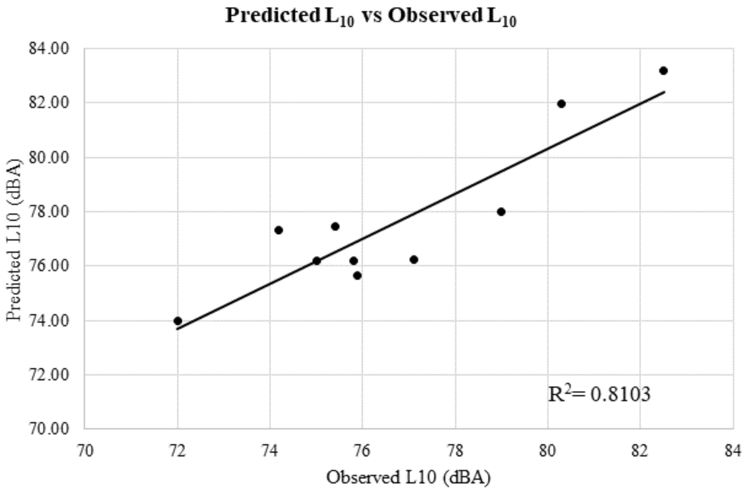


**Fig. 12.** Predicted vs Observed L10

### 3.4 Relative Importance of Input Variables

Relative importance of input variable was calculated to comprehend the level of contribution of each input variable. Here connection weights algorithm (Olden et al., 2004) is used to rank the input variables. The relative importance of an input variable can be determined using the following equation:

$$RI_x = \sum_{y=1}^{m} W_{xy}\, W_{yz}$$

Where $RI_X$ is the relative importance of input neuron x, $\sum W_{xy} W_{yz}$ is the sum of product of final weights of the connection from input neuron to hidden neurons with the connection from hidden neurons to output neuron, y is the total number of neurons in hidden layer, and z is output neurons. This approach relies on estimating of the final weights of the network, which are obtained from the training of the model.

**Table 5.** Final connection weights

| | H1 | H2 | H3 | H4 | H5 | H6 | H7 |
|---|---|---|---|---|---|---|---|
| | | | Input-Hidden | | | | |
| Input 1 (HV) | -0.205 | -0.205 | -0.205 | -0.205 | 0.205 | -0.205 | 0.205 |
| Input 2 (MV) | -0.050 | -0.060 | -0.050 | -0.050 | 0.050 | -0.050 | 0.050 |
| Input 3 (LV) | -0.140 | 0.493 | -0.140 | -0.140 | 0.140 | -0.140 | 0.140 |
| Input 4 (NMV) | -0.009 | 0.140 | -0.009 | -0.009 | 0.009 | -0.009 | 0.009 |
| Input 5 (RW) | 0.017 | -0.156 | 0.017 | 0.017 | -0.017 | 0.017 | -0.017 |
| | | | Hidden-Output | | | | |
| Output 1 (Leq) | -0.153 | 0.153 | -0.153 | -0.153 | 0.153 | -0.153 | 0.153 |
| Output 2 (L10) | -0.244 | 0.244 | -0.244 | -0.244 | 0.244 | -0.244 | 0.244 |

**Table 6.** Connection weights products, relative importance and rank of inputs

| Input | H1 | H2 | H3 | H4 | H5 | H6 | H7 | Sum | Relative Import. | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.081 | -0.08 | 0.081 | 0.081 | 0.081 | 0.081 | 0.081 | 0.407 | 40.4% | 2 |
| 2 | 0.020 | -0.024 | 0.020 | 0.020 | 0.020 | 0.020 | 0.020 | 0.096 | 9.5% | 3 |
| 3 | 0.056 | 0.196 | 0.056 | 0.056 | 0.056 | 0.056 | 0.056 | 0.531 | 52.6% | 1 |
| 4 | 0.003 | 0.056 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.076 | 7.5% | 4 |
| 5 | -0.007 | -0.062 | -0.007 | -0.007 | -0.007 | -0.007 | -0.007 | -0.102 | -10.1% | 5 |

Results suggest that light vehicles contributed the most to the noise level in the sampling points. Second most relative importance was given to heavy vehicles. It can be interpreted as vehicles like buses and motorcycles are more prone to honking, they contribute more to noise pollution. The observed locations had a large quantity of light vehicles like motorcycle and auto-rickshaw (on average 34% of total vehicle volume), so it is possible that this type of vehicle produced more noise. In addition, the engines of auto-rickshaws are very loud. Motorcycles were seen large in numbers, and from field observation it can be said that motorcycle drivers have heavy honking tendencies.

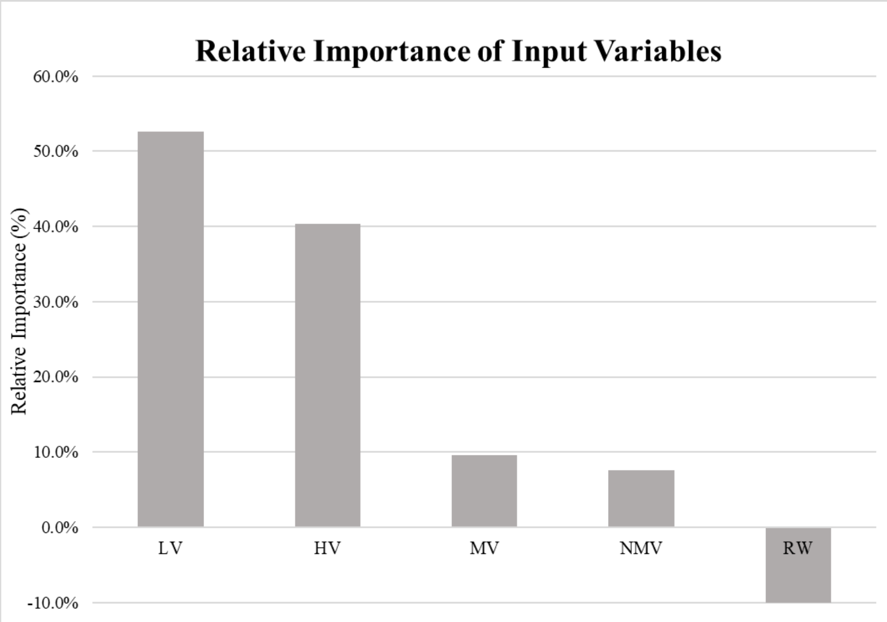


**Fig. 13.** Relative importance of input variable

# 4 Conclusion

Equivalent noise level near noise sensitive areas like educational institute and hospitals were found to be higher than the limit set in ECR 1997. The highest $L_{eq}$ was 84 dB and the lowest was 66 dB. The ANN model suggested a moderate correlation between inputs and outputs (0.75). According to the analysis on relative importance of input variables, light vehicles like motorcycles and auto-rickshaws contribute the most to noise pollution. This information is also supported by field observations, as light vehicles were the second-most common type of vehicle on the road, and motorcycle riders were seen to be particularly prone to frequent honking. Additionally, loud engine noise from auto-rickshaws increases pollution. Traffic noise was not the only source of noise pollution, as the presence of hawkers, construction sites, and machinery also contributed to increase overall noise level.

It should be mentioned that the study had a few limitations that may guide further research. The performance of the model is more likely to be enhanced by a larger dataset. The utilization of continuous 24-hour data gathering may yield more accurate insights into fluctuations in noise levels caused by the fluctuating number of vehicles throughout the course of the day. This research examined the scenario of free flow of traffic. Traffic variables including disrupted traffic flow may be deemed worthy of investigation in subsequent studies. Relative importance of input variables was found using the connections weight algorithm. Other methods can also be tried in the future to compare the results and find the best method for this type of dataset.

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