A MAJOR PROJECT REPORT ON

APPLICATION OF ARTIFICIAL NEURAL NETWORK IN TRAFFIC NOISE POLLUTION MODELLING

Submitted in partial fulfillment of the requirements

For the award of the degree of

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IN

ENVIRONMENTAL ENGINEERING

Submitted by

ANUJ KUMAR

2K13/ENE/11

Under the Guidance of

Dr. Rajeev Kumar Mishra

Assistant Professor

Department of Environmental Engineering

DEPARMENT OF ENVIRONMENTAL ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(FORMERLY DELHI COLLEGE OF ENGINEERING)

NEW DELHI - 110042.

CANDIDATES'S DECLARATION

I hereby declare that the work being presented in the dissertation title "**APPLICATION OF ARTIFICIAL NEURAL NETWORK IN TRAFFIC NOISE POLLUTION MODELLING"** in partial fulfillment of the requirements for the award of degree of **Master of Technology in Environmental Engineering,** submitted in the department of Environmental Engineering, Delhi Technological University (formerly Delhi College of Engineering) New Delhi, is an authentic record of my own work and carried out by me under the supervision of Dr. Rajeev Mishra, Assistant Professor, Department of Environmental Engineering, Delhi Technological University (formerly Delhi College of Engineering), New Delhi.

The matter embodied in this dissertation has not been submitted by me for the award of any other degree or diploma.

Delhi

Dated: July 2015 Anuj Kumar

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

Prof. A.K Gupta
Head of Department,
Department of Environmental Engineering
Delhi Technological University
New Delhi- 110042

Dr. Rajeev Kumar Mishra
Assistant Professor,
Department of Environmental Engineering
Delhi Technological University
New Delhi- 110042

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Anuj Kumar

Roll No. 2K13/ENE/11

ABSTRACT

This research has been motivated by the fact that present road traffic noise prediction models have not been improved since their development in the 1970s and 1980s, although road traffic noise nuisance is a significant and growing issue in India and elsewhere as the number of vehicles on roads is increasing day by day.

Noise is a global problem due to several factors: the increase in the number of per capita vehicles, the increase in demographic density, appliances and vehicles capable of generating loud noise, and also the fact that society is getting used to higher noise levels. Since 1972, when the WHO classified noise as a pollutant, most of the industrialized countries have decided to regulate noise through laws or local regulations.

In this study Artificial Neural Network (ANN) has been applied to predict noise pollution level in Delhi, capital city of India. Factors that predominantly influence noise pollution level in a traffic noise model framework were classified into two categories: traffic volume and traffic speed. Traffic volume, traffic speed and noise level data of traffic were collected at six identified locations in the city. The structure of the model selected consisted of input variable as 2W, 3W, Car, Jeep, Van, Bus, Truck, and Leq as output variable and corresponding traffic speed on both sides of the road were taken as input data and Leq as output variable. Models based on forward-propagation neural network were trained, validated and tested using the data collected through field studies.

All other data collected were the position of the measurement station, the geographical situation between the noise source and the measurement station, wind speed and direction, air temperature and relative humidity, and time of day.

The model was selected by varying the number of hidden neurons from 3 to 10. The best model was selected on the basis of Mean Square Error (MSE), which was in present case of 3 hidden neurons. The model selected can be applied for the prediction of Leq level.

It is shown that the artificial neural networks can be a useful tool for the prediction of noise with sufficient accuracy in the observed time intervals.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
Leq	Sound Pressure Level in dB(A)
L10	Sound level exceeded for 10% of the time
L50	Sound level exceeded for 50% of the time.
L90	Sound level exceeded for 90% of the time
MSE	Mean Square Error
MAE	Mean Absolute Error
r	Coefficient of correlation.
ANN	Artificial Neural Networks
CPCB	Central Pollution Control Board
CRRI	Central Road Research Institute
MORTH	Ministry Of Road Transport And Highways.
MoEFCC	Ministry of Environment, Forest and Climate Change
C/J/V	Car, Jeep and Van
B	Bus
T	Truck
2W	Two wheeler
3W	Three wheeler
N	North
S	South
E	East
W	West

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Chapter 1: - Introduction

1.1 General.

Noise can be defined as any unpleasant, unwanted or disturbing sound and is very high subjective feeling. Noise affects people's ability to talk to one another, hear threats around them, enjoy recreational pursuits and Learn and concentrates. Noise from roads depends on type of traffic, number of vehicles, number of large vehicles, location and the height of buildings and other noise barriers and the condition of surface of the roads.

Due to increasing motorization, construction of flyovers and growth in transport system, the noise level has been exceeded the prescribed limits in many of the Indian cities. The health entanglement of high noise levels are being identified such as hypertension, sleeplessness, mental stress, etc. because to these adverse effect of high noise level, it is important to assess the impact of traffic noise on residents and on road users. The present work is an effort to quantify and analyze the traffic noise emissions in various locations in Delhi. Field measurements were carried out to understand and assess various aspects of the impact of noise on the social lives of residents and road users of Delhi.

Noise pollution has been linked to a variety of health conditions in both occupational and community studies. Excess noise levels are a well-recognized cause of hearing loss. Moreover, noise pollution has been linked to cognitive deficits, sleep disturbance, heart disease, and diabetes. The health impacts of excess noise in the environment may be deleterious to children. While the mechanism linking noise to health is not fully understood, the association may in part be explained by stress responses. Noise is not uniformly distributed in urban settings. Excess noise pollution commonly near traffic, industry or transportation systems and impacts individuals living in such areas. In this study noise pollution has been choosen because it is believed that low income populations, accepts to live in less desirable housing conditions and can compromise living in areas where noise pollution is a prominent issue due to vehicular traffic.

1.2 Sources of Noise.

Noise pollution is a by-product of urbanizations, industrialization and modern civilization. Broadly the noise pollution can be divided into two sources, i.e. industrial and non- industrial sources. The industrial source comprise the noise from various industries and big machines. On the other hand non- industrial source of noise includes the noise created by transport/vehicles. Most leading noise sources categories are road traffic, aircrafts, railroads, construction, industries and noise in the buildings.

Road traffic noise can be separated into bulk traffic noise and intermittent traffic noise (Victoria EPA, 2002). In general, the traffic volume, traffic composition, traffic speed, gradient of the road, and the number of lanes of the roads all accord to the variance in noise levels from the road traffic. Further the noise itself is mainly created by a vehicle's engine, brake, tyre-road interaction, exhaust system, and aerodynamic effects (Figure1.1).

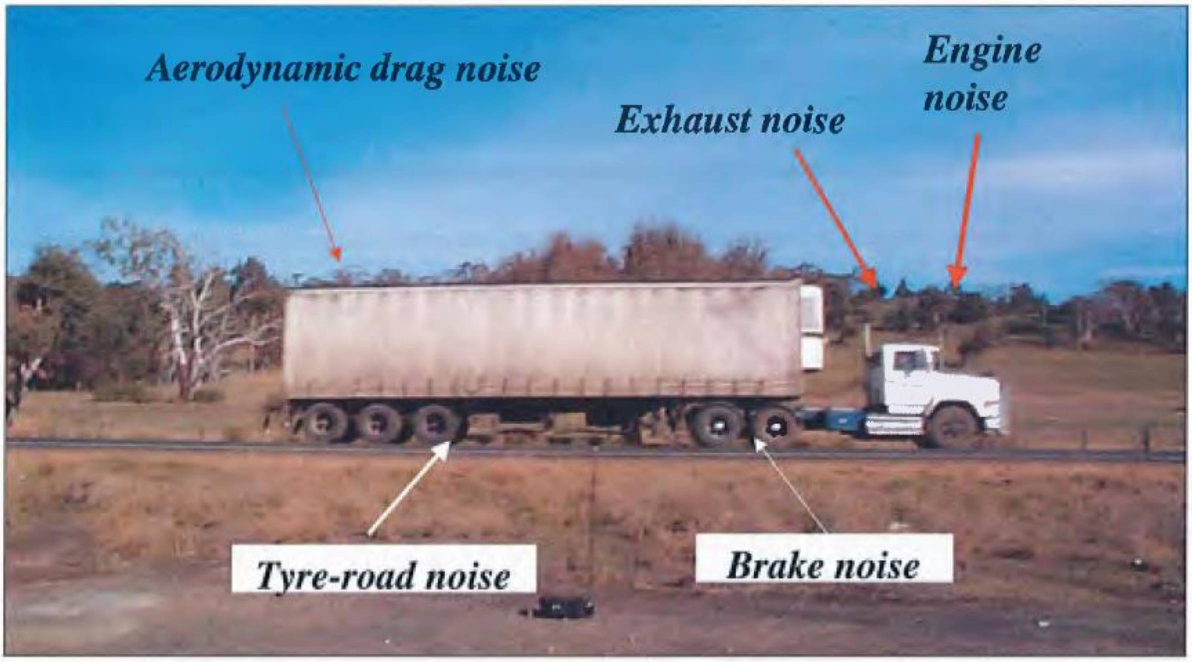

Figure 1.1: Principal sources of noise from a vehicle.

Bulk traffic noise is the component of the total road traffic noise which is roughly sustained in nature, which results from the overall effects of noise emissions from travelling traffic. At low traffic speeds, maximum of road traffic noise is generated by vehicle engines, exhausts, transmissions and brakes. And when the speed of the vehicles increases, noise from the interaction between road and the tyres increases and, at speeds near about 70 km/h and above, this becomes the supreme component of the bulk traffic noise. Air disturbances by moving vehicles at higher speeds also becomes an important factor. Intermittent traffic noise sources are individual vehicles and generally present itself as an unwanted noise of a usually short-term nature, covered on the background bulk traffic noise.

Various sources of intermittent traffic noise includes the following:

• heavy vehicles, which are inherently louder than medium or light vehicles

• modified cars and motorcycles

• truck air brakes

• exhaust systems

• vehicle horns.

Stop-start braking and acceleration of vehicles departing from traffic lights are also well known sources of intermittent noise. On the hills, the noise of braking and increasing the speed of engines in low gear also stand out from the steady bulk traffic noise. Heavy vehicles contribute more than medium and light vehicles to the overall traffic noise level. In the case of heavy vehicles which are not fully loaded, noise levels can be generated by vibration, and rattling.

1.3 Noise Pollution scenario in India.

Various technological developments has resulted in vehicles creating less noise, but the increment in the traffic and noisy period has nullified the reduction. Noise pollution has always been a problem, but nowadays it has become a major problem. According to a new government report, a great amount of noise is being produced on the streets of Delhi daily and most of it is caused by unregulated and overloaded trucks. Delhi noise level has been marked as 16 times higher than the "prescribed limits" by the Central Pollution Control Board (CPCB). The total number of registered motor vehicles from year 1951 to 2012 are mentioned in Table1.1 and the noise levels in Delhi have been compared from 2010 to 2014 in Table 1.2.

Table 1.1: Composition of vehicles Population (% of total) during year 1951-2012

As on 31st March	Two Wheelers	Cars, Jeeps & Taxis	Buses	Goods Vehicle	Other Vehicles	Total
	(as percentage of total vehicle population)					(Million)
1951	8.8	52	11.1	26.8	1.3	0.3
1961	13.2	46.6	8.6	25.3	6.3	0.7
1971	30.9	36.6	5	18.4	9.1	1.9
1981	48.6	21.5	3	10.3	16.6	5.4
1991	66.4	13.8	1.5	6.3	11.9	21.4
2001	70.1	12.8	1.2	5.4	10.5	55
2002	70.6	12.9	1.1	5	10.4	58.9
2003	70.9	12.8	1.1	5.2	10	67
2004	71.4	13	1.1	5.2	9.4	72.7
2005	72.1	12.7	1.1	4.9	9.1	81.5
2006	72.2	12.9	1.1	4.9	8.8	89.6
2007	71.5	13.1	1.4	5.3	8.7	96.7
2008	71.5	13.2	1.4	5.3	8.6	105.3
2009	71.7	13.3	1.3	5.3	8.4	115
2010	71.7	13.5	1.2	5	8.6	127.7
2011	71.8	13.6	1.1	5	8.5	141.8
2012	72.4	13.5	1	4.8	8.3	159.5

Source: MORTH.

Table 1.2: Ambient Noise Level in Delhi from 2010 to 2014

S.No.	Loctaion	Average Noise Level in dB (A) Leq				
		2010	**2011**	**2012**	**2013**	**2014**
1	**Lajpat Nagar**	63	67	58	56	-
2	**Mayur Vihar**	63	79	48	60	69
3	**Pitam Pura**	58	58	56	61	53
4	**Kamla Nagar**	56	58	61	63	59
5	**Dilshad Garden**	56	56	58	59	50

6.	**Connaught Place**	62	64	64	69	67
7.	**I.T.O**	65	72	70	67	-

Source: CPCB.

1.4 Health effects of Noise Pollution.

Noise may damage the human hearing efficiency and neuron cells of brain of human body. Other effects due to noise are constant stress, fatigue and hypertension, sleeping disorders, cardiovascular disease. Wildlife also faces more problems due to noise pollution as compared to humans since they are more sensitive to sound.

Health experts have sent the alarm bells ringing for the residents of South Delhi. Doctors have alerted that exposure for a long time to high noise levels can affect their hearing abilities to the extent that they would get dependent on hearing aids.

Dr Vidit Tripathi of Fortis Hospital, Vasant Kunj, said that "If you are exposed to noise above 70 decibels for more than five to six hours a day, your hearing will get affected. But if it exceeds over 85 dB(A), it will have a damaging effect on your hearing and you may soon be going for a hearing aid. This phenomenon is getting more common to not only heavy traffic South Delhi roads, but also across the whole city, where the main arteries are passing through the commercial and residential spaces

"In fact, the most affected one are children sleeping at night, who get disturbed when a tyre burst suddenly or the screeching sound of vehicles when brakes are applied suddenly," Kalavati, a housewife staying in the CSIR Scientist Apartment at Ashram, told. She also added: "It is very difficult to adjust to the noise the trucks make when they take over the flyover routes. Infact we have gradually got adjusted to the daytime noise, but nights are a nightmare as honking doesn't stop beside all traffic regulations."

The CRRI (Central Road Research Institute) study accessed by Mail Today points out that honking contributes three times what the normal traffic does at an intersection. Ashram is the worst example for this. Health experts warn that perennial exposure to loud noise levels leads to erratic blood pressure, depression, sleeping problems and nervousness all leading to a sudden strike as hormonal changes go unnoticed.

1.5 Emission Norms and Standards.

Emission norms for noise pollution are laid down in all developed and most of the developing countries. The maximum limits of noise emission for various vehicles in India are given in Table 1.3 and the ambient Noise Standards prescribed by the Central Pollution Control Board are given in Table 1.4.

Table 1.3: Maximum Limits of Noise Emission from various vehicles.

Vehicle Category	Max permissible Noise Limit
Two wheelers Petrol driven	80 dB (A)
Cars, Petrol driven three-wheelers and diesel driven two wheelers	82 dB (A)
LCVs including diesel driven three wheelers with gross weight upto 4000 kgs.	85 dB (A)
Commercial vehicles with gross weight above 4000 kgs and upto 12000 kgs	89 dB (A)
Commercial vehicles with gross weight above 12000 kgs	91 dB (A)

Source: MoEFCC

Table 1.4: Ambient Noise level Standards prescribed by the Central Pollution Control Board.

Category of Area / Zone	Limits in dB(A) Day Time (Leq)	Limits in dB(A) Night Time (Leq)
Industrial area	75	70
Commercial area	65	55
Residential area	55	45
Silence Zone	50	40

Source: CPCB

Note:-

1. Day time means from 6.00 a.m. to 10.00 p.m.

2. Night time means from 10.00 p.m. to 6.00 a.m.

3. Silence zone is an area comprising not less than 100 meters around hospitals, courts, educational institutions, religious places or any other area which is declared as such by the competent authority.

4. Mixed categories of areas may be declared as one of the four above mentioned categories by the competent authority.

1.6 Modelling of Traffic noise

Traffic noise prediction models are helps in the design of highways and other roads and sometimes in the assessment of existing or forecasting the changes in traffic noise conditions. They are commonly needed to predict sound pressure levels, specified in terms of (Leq) L10, L50, L90 etc.

Many road traffic noise prediction models have been developed in the last few years. The development of models to predict traffic noise started in the late 1960s and early 1970s, when road traffic noise first became a concern that was wide spread in nature to prompt such research work. Usually these kind of models are developed taking into account mainly traffic flow, traffic category (light and heavy vehicles), features of the road surface, distance between carriage and receivers. The objective of using a Traffic Noise Model (TNM) is twofold: on one side it can be used in the designing of new road infrastructures in order to estimate the acoustical impact and to avoid post construction mitigation actions that often leads to greater cost; on other side it can be used on an existing road network, so that the measurement campaign can be minimized and can be used just for the tuning of the model.

1.7 Introduction to Artificial Neural Network

An ANN is an information processing paradigm that is inspired by the way a biological nervous system, such as the brain, process information. In this information processing system, the elements called neurons, processes the information. It resembles the brain in two respects:

i. Knowledge is acquired by the network through a learning process

ii. Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

An artificial neuron is characterized by:

1. Architecture (connection between neurons)
2. Training or learning (determining weights on the connections)
3. Activation function

All neural networks share some basic features. They are composed of simple processing elements, known as neurons. These elements take data from source as input and compute an output dependent in some well defined way on the values of inputs, using an internal transfer (i.e. Activation) function. These neurons are joined together with some weights. Data flows along these connections and is scaled during transmission according to the values of weights. The relationship between the input signals X_0, X_1... X_n of neuron j and its output Y_j is given by

$$I_j = \sum_{i=0}^{n} W_{ji} X_i \qquad \text{........................(1.1)}$$

$$Y_j = f(I_j) \qquad \text{........................(1.2)}$$

Where W_{jo}, W_{j1},..., W_{jn} are the respective synaptic links, which are associated with weights. A bias weights of neuron j, I_j are the linear combiner output acts exactly as a weight on a connection from a unit due to input signals and f is the activation function whose activation is always 1. The arrangement of neurons into layers and the pattern of connection within and in-between layers are generally called the architecture of the net. The process of modifying weights according to the connections between the network layers, with the objective of achieving the expected output is called training a network.
The internal process that takes place when a network is trained is called learning. Generally the three types of training are as follows:

Supervised training: Supervised training is the process of providing the network with a series of sample inpts and comparing the output with the expexted responses. The trining continues until the network is able to provide the expected response. In a neural net, for a sequence of training input vectors there may exist target output vectors. The weights may then be adjusted according to a learning algorithm. This process is called supervised training.

Unsupervised training: In a neural network, if for the input vectors, the corresponding target output is not known in a neural network, the training method adopted is called unsupervised training. A network may modify weights so that the most similar input vector is assigned to the output unit. The network is found to form a exemplar or code book vector for each cluster formed. This is the method adopted in the case of self-organizing feature maps, adaptive resonance theory, etc. The training process extracts the statistical properties of the training set and groups similar vectors into classes.

Reinforcement Learning: In this method, a teacher is also assumed to be present, but the right answer is not presented to the network. Instead, the network only gives an indication of whether the output answer is right or wrong. In this learning process, network attempts to learn the input-output mapping through trial and error with the view to maximize the performance index called the reinforcement learning signal. Reinforcement learning lies between supervised and unsupervised learning. It operates through continuing interactions between a learning system and the environment.

Weights: Weight is information used by the neural network to solve a problem. Neural networks consist of a large number of simple processing elements called neurons. These neurons are connected to each other by directed communication.

1.8 Objective of the study.

The objectives of this study are:-

1. To measure the ambient noise level at selected locations.
2. To observe the temporal variation of vehicles at selected locations.
3. To develop a model using Artificial Neural Networks.
4. To compare the observed and predicted noise level with the standards of ambient noise given by CPCB.

Chapter 2: - Literature Review

2.1 General.

The continuous growing of road noise facilitated the appearance of a new noise field that must be monitored. In our society, big governing unions like EU government start to get involved in such problems like noise because it medically affects the life of a big number of citizens. The first step to be taken in solving the problem it is to visualize it, to analyze it to understand it better. One of the best ways of handling traffic noise is to provide noise maps for all major EU cities, which was already undertaken by the EU. For example, there are online noise maps for London, present at http://www.noisemapping.org/.

2.2 Efforts made in India for Noise Pollution

In India, the earliest noise surveys were carried out by Panchoy et al, during the sixties. The result of these surveys found application in compiling the section on acoustics, sound insulation and noise control in national building code.

Gupta, Khanna and Gangil attempted to develop relationship between the vehicular noise and stream flow parameters in the year 1979. The state highway 45 passing through Roorkee was selected as the study area between Polaris intersections to Roorkee talkies intersection. The developed prediction equation for the noise level L_{10} is given below.

$$L_{10} = 18.092433 + 19.90357 \ X \ \log 10 \ (Q_w) \qquad dB\ (A)\ldots\ldots\ldots\ldots..(2.1)$$

Where, Q_w = traffic volume in EPCU/hr.

Gupta, Nigam and Hinsi analysed the traffic noise pollution for mixed traffic flow for various land uses. The data was collected in Roorkee on NH-45 which is very important highway carrying a high volume on three selected sites. A computer program was developed in FORTRAN IV to evaluate the noise parameters. From the study it was found the value of 'K' reported by Robinson does not match for mixed traffic flow (highway heterogeneous flow) and varies between 2.37 to 3.54 as ageist value of 2.56

Srivastava, Gupta and khanna evaluated the environmental noise pollution on the NH-45 between Ghaziabad and Roorkee in continuation of their earlier study. Gupta, Srivastava and khanna have developed a computer software package name "traffic noise analysis package" (TNAP) in the year 1993. This package has got three different alternative options. Using first option the various noise parameters like L_{10}, L_{50},L_{90} and Leq etc. may be calculated. Second option is for predicting the noise level Leq. Leq can be predicted for a given classified volume per hour and at a desire distance (in m) from centre of traffic flow. The third option provides facility to obtain the combine noise level of a mixed traffic flow stream by giving their individual noise levels as input data.

Kumar Vimal carried out a study in Delhi to study the urban noise scenario and has developed various useful correlations between various traffic parameters like traffic volume, traffic speed, and distance from pavement edge and the equivalent sound level Leq. Form the correlations developed. It is possible to predict the impact of traffic developments in terms of noise pollution in future and timely measures for control can be implemented. The developed prediction equation for the noise level Leq (1h) is givn below.

$$Leq\ (1h) = 47.45 + 8.58 \times Log(Q_w) - 0.14d \qquad dB(A) \ldots\ldots\ldots\ldots (2.2)$$

Where Q_w= Traffic volume in EPCU/hr.

Kumar, P. carried out individual vehicle noise level study for proper categorization of vehicles and developed basic noise level equation for each vehicle type. He further caliberted noise prediction mode for traffic noise prediction for Indian conditions.

2.3 ANN based Noise Pollution Case Studies

Several attempts have been made to predict and model road traffic noise mathematically and statistically by different researchers. Due to the capability of neural networks to model nonlinear systems, Cammarata et al. (1993) studied the functional relationship between road traffic noise and related physical parameters. A back propagation network was applied to extract the functional relationship between particular road parameters (number of vehicles, the average height of buildings, road width) and the level of sound pressure. The neural network approach was compared with those provided by a selected relationship found in the literature and showed that the agreement between predictions and measurements are much more favorable to a neural network than to linear regression approach Cammarata et al. (1993). One limit of the neural method proposed, is its dependence on the acoustic measurements made. Errors in the measurement or incorrect interpretation make it impossible to supply (in the learning phase) the network with a set of data which can significantly represent the correlation between the parameters taken into consideration and the sound pressure level.

In addition, during the production phase it is difficult to check whether a neural network output value (which is rather different from the value measured) is to be attributed to a defect in the learning phase or to an error in measurement. To present a strategy based on neural networks for the automatic recognition of acoustic measurements affected by errors they proposed Camimtarata et al. (1993) a neural approach to filter data provided by acoustic measurements. It was based on the use of a Kohonen Self-organizing Map network, which receives correct acoustic measurements in the learning phase. The Kohonen neural network learning on the basis of this set of measurements would allow the network to be used as a filter. Having received a set of acoustic measurements in the input, it would be able, in the production phase, to discard any acoustic measurements which were insignificant or affected by errors.

Use of ANN for the first time in the field of traffic noise modeling was carried out by Cammarata et al. (1995). They proposed a neural architecture made up of two cascading levels. At first level a supervised classifying network, named learning vector quantization (LVQ) network, filters the data, discarding all wrong measurements, while on the second level Back Propagation Network (BPN) predicts the sound pressure level. Results obtained by the comparison of the BPN approach with those provided by selected relationships found in relevant literature, it was concluded that ANN based BPN model was capable of predicting traffic noise more accurately and effectively as compared to empirical and regression models. Dougherty (1995) presented a review based on the application of neural networks to the transportation system. On author's best knowledge, the theoretical extension of ANN in the direction of noise modeling is limited to case studies only. Most of the studies conducted in various parts of the world on the application of ANN for noise modeling purpose are of case study types, which use a different architecture of ANN, various parameters and characteristics depending upon particular country or area conditions specifically. A new and sophisticated method, called artificial neural networks, was used for modeling and predicting noise levels. This method provides flexibility, accuracy and some amount of fault tolerance in noisy and changing environments. It has a potential future in other fields of instrumentation and measurement science, and has an independent modeling structure (Patra *et al.*, 1998).

Cammarata et al. (1995) proposed use of a neural architecture made up of two cascading levels. At the first level a supervised classifying network, learning vector quantization (LVQ) network, filters the data, discarding all the wrong measurements, while at the second level the BPN predicts the sound pressure level.

A method based on fuzzy logic for urban noise prediction is briefly described in (Aguilera de Maya, 1997). The results obtained are not accurate enough, however, in the section of conclusions it is indicated that the results of the fuzzy model have been contrasted with actual data from measurements made in the prediction scenarios and it has been proved to be highly successful.

Caponetto et al. (1997) put forth a method based on genetic algorithms, which seeks the optimization of fuzzy rules based system for environmental noise prediction. The obtained results demonstrate the success of their method.

Wu and Zhang (2000) concluded that the artificial neural network provides a new method for traffic noise prediction. Based on the traffic noise data measured near a highway in China, an artificial neural network model was formed to predict further traffic noise levels. It was found that the predicted data from ANN model were in good agreement with measured data.

Couvreur & Laniray (2004) describes an Automatic Noise Recognition System. The system is based on neural networks and Hidden Markov Models and is able to distinguish, from 1000sound recordings, between two sounds: horn or motorcycle engine. The neural network phase includes a multilayer perceptron ANN, where the coefficients were obtained by supervised training. Another noise classifier is developed in (Berg, 2002), which recognizes the sounds of planes, with the use of neural networks. The neural network is built with a back propagation architecture with three neurons in the hidden layer.

Carter et al. (2000) used a combination of image processing and neural networks in their demonstration automated multiple-lane traffic survey system that analyzed real-time feed from cameras used to monitor traffic on the main roads through Hobart, Tasmania. Expert systems, which are decision-making tools, have long found application in controlling traffic lights.

In (Beritelli et al., 2000) an urban noise classifier based on fuzzy techniques is presented. Considering a set of acoustic characteristics, it tries to distinguish among seven categories: bus, car, rail, construction works, people talking, street and factory. Several works (Gaunard et al., 1998; Couvreur et al., 1998; Ma et a., 2003a,b) develop a Hidden Markov

Model based noise classifier system. These publications describe how a Hidden Markov Model can be used to develop a recognition system based on the ambient noise frequency analysis. A preprocessor provides frequency representation in time of the audio signal, which is then used by a classifier. The classifier makes a decision depending on the nature of the noise source, according to the characteristics given by the preprocessor. Two ways of improving the performance of automatic noise recognition are presented in (Betkowsa et al., 2005). Firstly, it is proposed the minimization of the number of parameters of a Hidden Markov Model based noise classifier, in order to reduce its complexity. Secondly, it seeks to combine the results of different recognition systems, applying the method of combining expert (MoE, Mixture of Experts). It uses neural networks, which are applied to combine the results and make a final decision on the status of the signal.

Artificial neural networks have been used as predictors for many regression problems. Knowing how well predictions match the real world is crucial to some of them, and so many research groups have developed strategies to tackle this problem (Webera *et al.*, 2003). A statistical model of road traffic noise in an urban setting which is based on the fact that percentage of heavy vehicles plays an important role over road traffic noise emission was developed by Calixto et. al., (2003).

Considering the position of the measurement station, geographical situation between noise source and measurement station, wind speed and direction, air temperature and relative humidity, and time of day, use of artificial neural networks to model variation of noise levels from traffic around the educational campus area has been reported (Yasar et al., 2004). To have both the capabilities of learning and interpretability in networks and fuzzy logic are used for predicting the effects of noise pollution on human work efficiency Zaheeruddin et al., (2004). A Neuro fuzzy computing system provides system identification and interpretability of fuzzy models and learning capability of neural networks in a single system. The Neuro-fuzzy model was developed for predicting the effects of noise pollution on human work efficiency as a function of noise level, type of task, and exposure time.

The most prolific authors who have dealt with techniques based on fuzzy logic modeling of environmental noise are Botteldooren and Verkeyn (Botteldooren & Verkeyn, 2001; Botteldooren & Verkeyn, 2002a,b,c,d,e; Botteldooren et al., 2002a,b; Botteldooren et al., 2003a,b; Botteldooren & Lercher, 2004). Their main field of study is the prediction of the noise annoyance level of people. For this reason, a fuzzy model is used in the majority of its proposals, looking for a set of rules that describe the fuzzy system. It deals with the study creating a fuzzy rule based system that predicts responses from the public about the noise annoyance caused by road and railway traffic noise.

Turkish standards allow up to 45 dB in places of study environment. Avsar et al., (2004) studied whether these standards are met using a multilayer perceptron neural network with noise data of 16 points in a Turkish campus. The neural network is built with seven inputs: position of the measuring point, distance from the source to the point of action, wind speed and direction, air temperature, relative humidity and time of day. The output is the descriptor A-weighted energy-equivalent sound pressure level (LAeq).

A multilayer perceptron (MLP) model was used for the modeling purpose. Results reveal that ANN can be applied successfully for noise prediction purpose. A comprehensive study on the assessment and ANN modeling of noise levels due to vehicular traffic flow for uninterrupted and interrupted traffic flow condition in Yavatmal city, Maharashtra State, India, was carried out (Parbat and Nagarnaik, 2007). ANN modeling was performed with input parameters including traffic composition (Bus/Truck, Light Commercial Vehicle (LCV), Two Wheeler (TW), Bicycle and Others), carriageway width, and distance of the receiver from pavement. Artificial neural network software Elite ANN (Pandhari pande and Badhe, 2002) was used for the development of MLP. It was found that ANN modeling is most probable solution for random samples of traffic noise data. A comparative study of logarithmic, linear regression, and neural models capable of predicting maximum A-weighted noise level ($L_{A_{\max}}$) for Tehran-Karaj express train was reported by Givargis et al. (2009). A model was developed on the basis of measurements from sampling locations at distances of 25 m, 45 m, and 65 m from the centerline of the track and at a height of 1.5 m. In the next step, the predictive capability of models has been tested on the data associated with the sampling locations, situated, respectively at distances of 35 and 55 m from the centerline of track at a height of 1.5 m. Another case study by Givargis et al. (2010) presented a basic and preliminary neural network model using a restricted database, assuming bituminous road surfaces with mean traffic speeds of less than 75km/h to predict 1-hour A-weighted equivalent noise level ($L_{A}eq,1_{h}$) for Tehran's roads at distances less than 4 m from the nearside carriageway edge and at a height of 1.4 m above the ground. Overall model efficiency was tested using non-parametric tests, such as the Wilcoxon matched- pairs signed-rank test for the training step and Kolmogorov-Smirnov test for two independent samples for validation step. Results of both studies indicate that the ANN approach can be applied to traffic noise prediction in Tehran.

In (Genaro et al., 2010) a neural network based model for urban noise prediction is developed. In this paper a selection of 12 street locations with different characteristics of the city of Granada (Spain) is carried out to obtain a representative sample of the complexity of urban streets with presence of road traffic. A set of 289 data vectors, each one with 26 components, was obtained. A total of 25 input variables were used (Torija et al., 2010a), being the only output variable the A-weighted energy-equivalent sound pressure level (LAeq). The results were compared to those obtained with mathematical models. It was found that the proposed ANN system was able to predict noise with greater accuracy, and thus was an improvement on these models.

Toriza et al., (2012) demonstrated a STACO model intended to predict the short term (5 min integration period) level and temporal-spectral composition of the sound pressure of urban sonic environments.

It has been observed that horn noise occurs with a frequency of 16 per minute and raises Leq by 12 dB (A). The recent studies by Kumar *et al. (2014)* and Sharma *et al. (2014)* have also tried to model the traffic noise by using ANN and regression approach.

Nucara *et al.* investigations revealed that the dynamic behavior of neural networks which allow complete and detailed description of the involved phenomena has found increasing applications in the research field.

Kalkat et al. (2009) have studied to improve the application of neural networks on the vehicle engine system for fault detecting and analyzing of engine oils. Three types of neural networks have been employed to find exact neural network predictors of vehicle engine oil performance and quality.

Yıldırım et al., (2008) have presented a noise analysis of passenger cars using artificial neural networks (ANNs). The research comprises the experimental analysis of car's engines and simulation analysis of noise parameters using ANNs.

Yıldırım et al. (2009) have presented an experimental design method for noise and vibration analysis of two car engines by feedforward and radial basis neural networks. Two types of car engines have been experimentally analyzed by using an intelligent data acquisition card with software. Behzad et al. (2007) have presented both numerical and experimental investigation of the noise emission level associated with two types of speed reducer for different dimensions and different speeds of vehicles and zero acceleration.

Yıldırım and Eski (2008) have presented a procedure for testing and evaluation on the sound quality of cars with varying running speed. Both experimental analysis and neural network predictor have been designed to model the system for possible experimental applications. A recurrent type network, which consisted of two types of neuron function in the hidden layer, has been used. The results of computer simulations and experiments show that the neural predictor algorithm gives good results at accommodating different cases and provides a superior prediction on two cars' sound analysis.

Taghavifar et al. (2013) showed that the ANN advantages are fast, precise and reliable computation of multi-variable, non-linear and complex computations compared to the mathematical conventional and numerical methods.

2.4 Health Effects Due to Road Traffic Noise.

Evans and Hygge in 2000 divided the effects of noise on human health and comfort into four categories depending on its duration and volume. They are –

(i) Physical effects such as hearing defects.

(ii) Physiological effects, such as increased blood pressure, irregularity of heart rhythms and ulcers.

(iii) Psychological effects, such as disorders, sleeplessness and going to sleep late, irritability and stress.

(iv) Effects on work performance, such as reduction of productivity and misunderstanding what is heard.

Zhao et al., (1993)Noise exposure has also been shown to be a significant determinant of hypertension prevalence in China, trailing only family history and salt use.

Liu et al., (2001) in a recent survey in the south- west province of Sichuan that involved 126,876 randomly selected individuals suggested an overall hearing loss prevalence of 3.28%, with 73% of the cases being senso- rineural. Liu et al., (1993) in the same province, the rate of profound deafness had been reported to be at 0.186%, with 35.6% of these cases being attributed to environmental factors.

Tang et al., (2001) In a study conducted at the beginning of the 21st century in Suzhou, a mid-size city in southeastern China, the prevalence of hearing loss was reported to be at 66.5% among urban seniors and 50.5% among their rural counterparts. While the rate of disease-related hearing impairment was similar in the two groups, the rates of presbycusis and noise-induced hearing loss (NIHL) was significantly different: 55.8% versus 43.4% and 6.5% versus 0.8% re- spectively, with the rate in the urban group being higher than that in the rural group.

A Sino-Japanese group studied hearing impairment among school age (7-17 years) children in a rural area in a northern Chinese province (Shandong) in 1996. Luo et al., (1996) founded that out of the 282 children studied, 56 (20%) were found to have abnormal hearing and more than half of the hearing loss ears either demonstrated a 4000 Hz notch or were dominated by high frequency loss. The prevalence of hearing loss in this group of Chinese children is significantly higher than young Japanese or even the normal data on young people in the same province in 1987.

Goines et al., (2007) stated that the World Health Organization (WHO) has documented seven categories of adverse health and social effects of noise pollution, whether occupational, social or environmental: hearing impairment, interference with spoken communication, cardiovascular disturbances, mental health problems, impaired cognition, negative social behaviors and sleep disturbances.

Van Cauter et al., (2008) stated that sleep is an important modulator of hormonal release, glucose regulation and cardiovascular function. In particular slow-wave sleep, the most restorative sleep stage, is associated with decreased heart rate, blood pressure, sympa- thetic nervous activity and cerebral glucose utilization, com- pared with wakefulness. During this sleep stage, growth hormone is released while stress hormone cortisol is inhib- ited. Spiegel et al., (2009) Experimental studies demonstrated that both sleep restriction and poor quality sleep affect glucose metabolism by reducing glucose tolerance and insulin sensitivity.

Knutson et al., (2013) Indeed, there is increasing evidence that quantitative and qualitative sleep disturbances may play a role in the development of cardiometabolic disease. A number of cardiovascular risk factors and cardiovascular outcomes have been associated with disturbed sleep: coronary artery calcifications, atherogenic lipid profiles, atherosclerosis, obesity, type 2 diabetes, hypertension, cardiovascular events.

Leger et al., (2014) Disturbed sleep has also been associated with increased frequency of violent acts as well as domestic violence, work and vehicle accidents, increased work absenteeism. Owens (2009) showed that as a result of sleep disturbances, children also suffer from impaired cognition and worsening of attention deficit hyper- activity disorder symptoms.

Basner et al., (2005) generated that Nocturnal environmental noise also provokes measurable metabolic and endocrine perturbations (increased secretion of adrenaline, noradrenaline, cortisol), increased heart rate and arterial pressure, and increased motility. These biological responses to noise during sleep are most of the time unnoticed.

Basner et al. showed that although these effects on sleep structure and continuity are relatively modest, they have a significant impact on subjective assessments on sleep quality and recuperation: Subjects experience their sleep as disturbed and with low recuperative value. Also, despite being most of the time in an unconscious state, subjects are able to distinguish between nights with low and high degrees of traffic noise exposure.

Chapter 3: - METHODOLOGY OF STUDY

3.1 General.

The data was collected form different locations in Delhi. The locations were choosen so as to represent different zones within Delhi like Residential, Commercial, Silence and Heavy Traffic zone. The parameters collected at all the locations were the ambient noise level, classified traffic speed, classified traffic volume, geometric parameters and the meteorological parameters like temperature, humidity, wind velocity, wind direction. Noise level meter and radar gun were the two instruments required for data collection from different locations.

3.2 Identification of Locations.

To measure the traffic noise pollution, the first task was site selection. Therefore, after performing several surveys of different areas and nature of noise problem in Delhi, six sites were selected where the continuous uninterrupted flow of vehicles were occurring. The sites selected were Karol Bagh, Uttam Nagar, Punjabi Bagh, Janpath, Laxmi Nagar, Madhuban Chowk. The selected locations and their land use pattern are depicted in Table 3.1. The map of Delhi showing the selected locations for field studies are presented in Figure 3.1.

Table 3.1 : Selected locations and their land use pattern.

S.NO.	Location Name	Land Use Pattern
1.	Madhuban chowk	Commercial and Residential
2.	Laxmi Nagar	Commercial and Residential
3.	Karol Bagh	Commercial and Residential
4.	Punjabi Bagh	Commercial and Sensitive
5.	Uttam Nagar	Commercial and Residential
6.	Janpath	Commercial

Fig 3.1: Map of Delhi Showing Identified Locations of Study.

3.3 Data Collection.

Following parameters were collected during Data collection.

1. Classified Traffic speed
2. Classified Traffic Volume
3. Ambient noise level
4. Meteorological parameters like temperature, humidity, wind velocity, wind direction.

5. Geometric parameters like road width, number of lanes, lane width, presence of divider and its width.
6. Miscellaneous information regarding type and condition of roadway etc.

3.3.1 Traffic Volume

Traffic volume studies were carried out at all the locations. At all the sites, traffic volume studies were conducted continuously for a period of twelve hours. Traffic volume data were manually recorded of every hour. And the data of all the locations has been presented in Appendix A.

3.3.2 Vehicle Speed Study.

Traffic speed study was carried out continuously for a period of twelve hours at all the identified locations. The classified traffic speed study was carried out for both the directions using radar gun. The spot speed data for all the identified locations is given in Appendix B.

3.3.3 Meterological Data.

The meteorological parameters which have a major effect on pollution are wind speed, wind direction, mixing height, ambient temperature, humidity, moisture content. The data on each of study day was obtained from Indian Meteorological Department, New Delhi. The values for the same are given in Appendix C.

3.2.4 Noise Pollution Measurements.

The ambient noise pollution data was collected continuously for a period of twelve hours at all the identified locations using Noise Level Meter.

Characteristics of Instrument:-

1. The SC260 is a user-friendly class two integrating sound level meter. It can be used either as an sound level meter or as an real time spectral analyser with 1/1 or 1/3-octave bands with class 2 filters.
2. The SC260 measures all functions simultaneously, including all the frequency weightings. Amongst these are all the functions necessary to calculate the basic indices for the acoustic evaluation of most countries in the world: S, F and I functions, equivalent continuous levels, impulsiveness indices, percentiles, sound exposure levels, short functions, peak levels etc.

3. The free memory space can also be configured as a circular memory. Along with the possibility of downloading data simultaneously to its storage, makes the SC260 into the perfect platform for permanent acoustic monitoring.
4. The microphone is detachable. Thus it can be therefore disconnect and moved away from the SC260 by means of an extension cable (CNRITV). This instrument can be complemented with an outdoor kit for making measurements in the open air.
5. Sound level meter is shown in Figure 3.2.

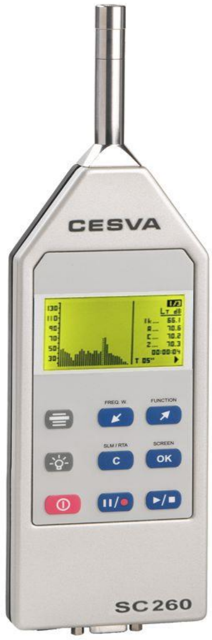

Figure 3.2: Sound level meter.

Data was collected at an interval of one minute. The hourly Leq values collected for all the identified locations are given below. Also the hourly Leq peak, L_{10}, L_{50}, L_{90} values for all the locations recorded at the time of data collection are described below.

- **Data collected at Laxmi Nagar:-**

  Data collected at laxmi nagar is depicted below in Figure 3.3 and in Table 3.2.

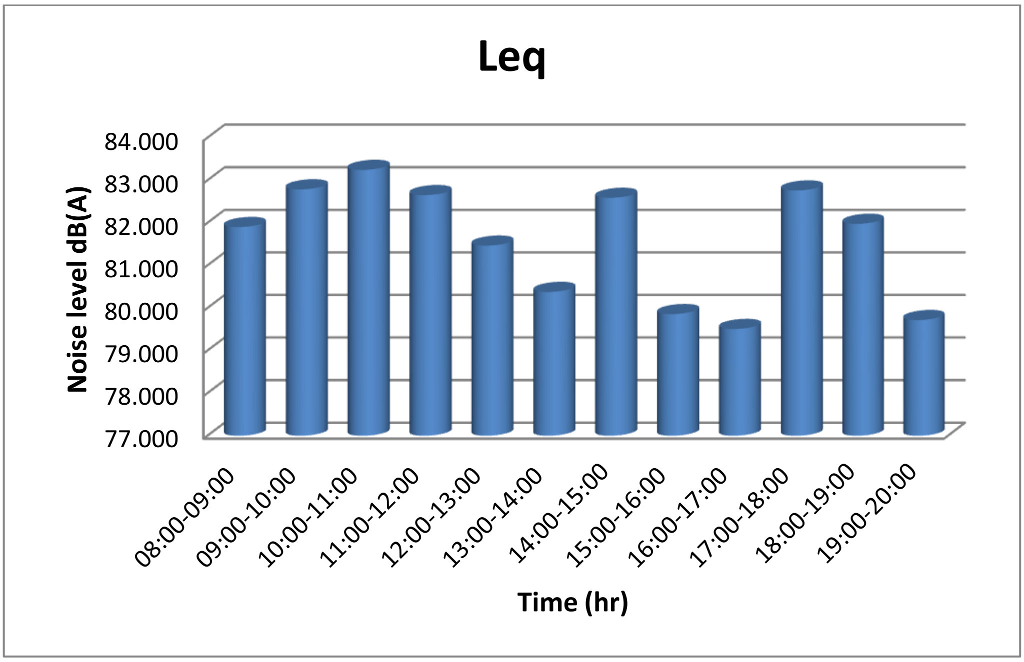

Figure 3.3: Temporal variation of Leq at Laxmi nagar

Table 3.2: Leq peak, L10, L50, L90 measured at Laxmi nagar

Time	Leq peak	L10	L50	L90
08:00-09:00	104	84	79	77
09:00-10:00	106	85	80	77
10:00-11:00	105	85	81	79
11:00-12:00	105	85	80	78
12:00-13:00	104	84	79	76
13:00-14:00	104	83	78	74
14:00-15:00	108	85	78	74
15:00-16:00	103	82	77	74
16:00-17:00	102	82	77	74
17:00-18:00	106	85	80	76
18:00-19:00	104	84	80	76
19:00-20:00	102	82	77	74

- **Data collection at Uttam Nagar:-**
  Data collected at Uttam nagar is been shown below in Figure 3.4 and in the Table 3.3.

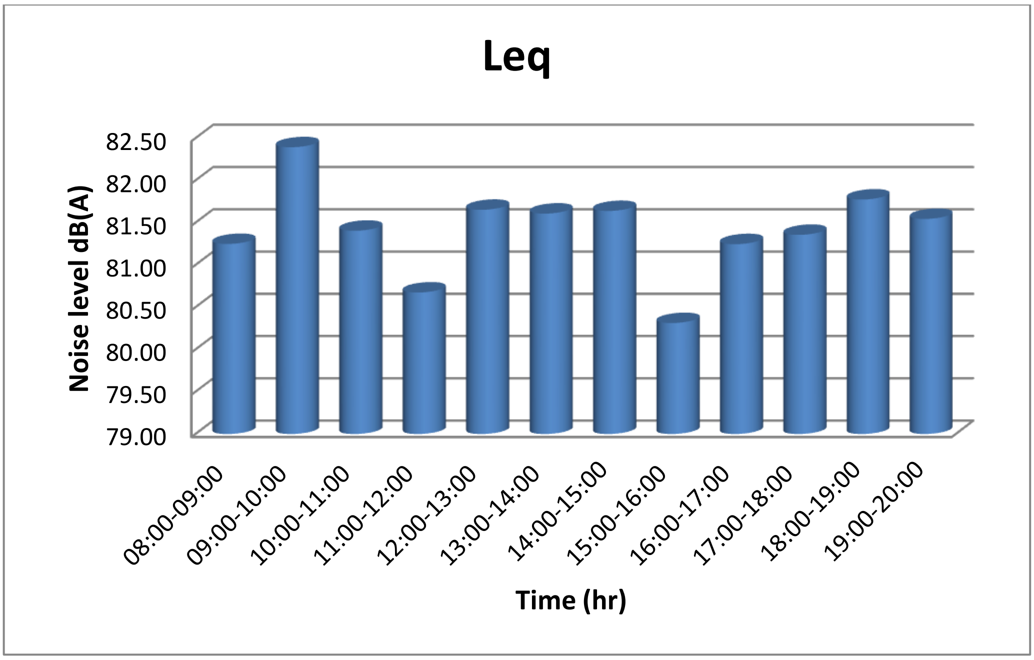

Figure 3.4: Temporal variation of Leq at Uttam Nagar

Table 3.3 : Leq peak, L10, L50, L90 measured at Uttam Nagar

Time	Leq peak	L10	L50	L90
08:00-09:00	104	84	79	75
09:00-10:00	105	85	80	76
10:00-11:00	105	84	79	76
11:00-12:00	103	83	78	75
12:00-13:00	106	84	79	75
13:00-14:00	105	84	79	75
14:00-15:00	105	84	79	76
15:00-16:00	104	83	78	75
16:00-17:00	108	84	79	76
17:00-18:00	106	84	79	76
18:00-19:00	106	84	79	76
19:00-20:00	106	84	79	76

- **Data collection at Karol bagh:-**

  Data collected at Karol bagh is been shown below in Figure 3.5 and in the Table 3.4.

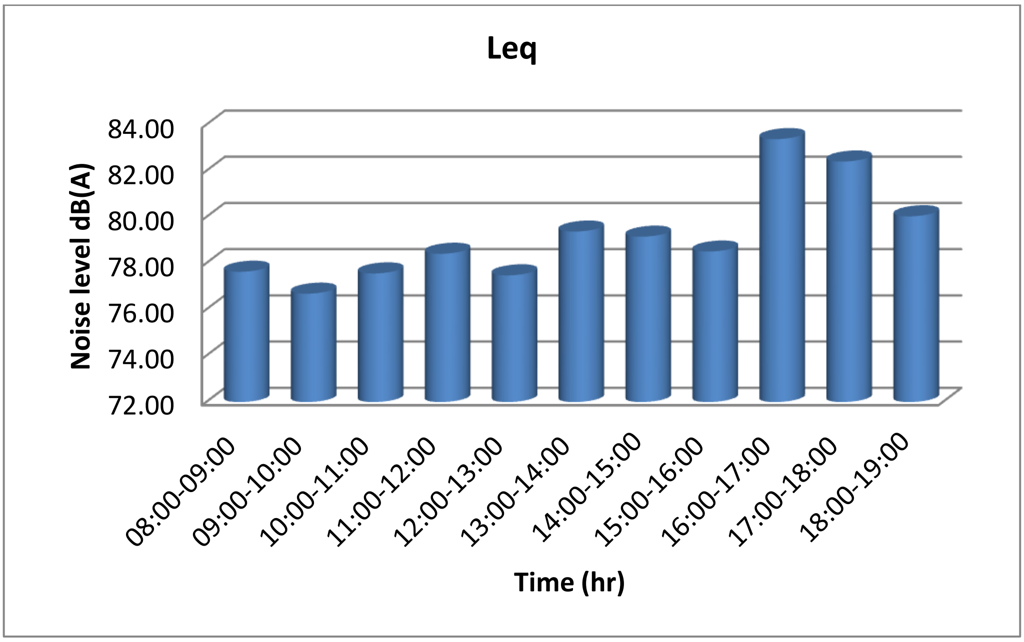

Figure 3.5: Temporal variation of Leq at Karol bagh

Table 3.4 : Leq peak, L10, L50, L90 measured at Karol bagh

Time	Leq peak	L10	L50	L90
08:00-09:00	100	80	75	71
09:00-10:00	98	79	75	71
10:00-11:00	100	80	76	71
11:00-12:00	101	81	77	73
12:00-13:00	99	80	75	72
13:00-14:00	103	82	77	73
14:00-15:00	101	81	77	73
15:00-16:00	102	81	76	73
16:00-17:00	105	86	81	77
17:00-18:00	105	85	80	76
18:00-19:00	103	83	78	74

❖ **Data collection at Punjabi bagh:-**

Data collected at Punjabi bagh is been shown below in Figure 3.6 and in the Table 3.5.

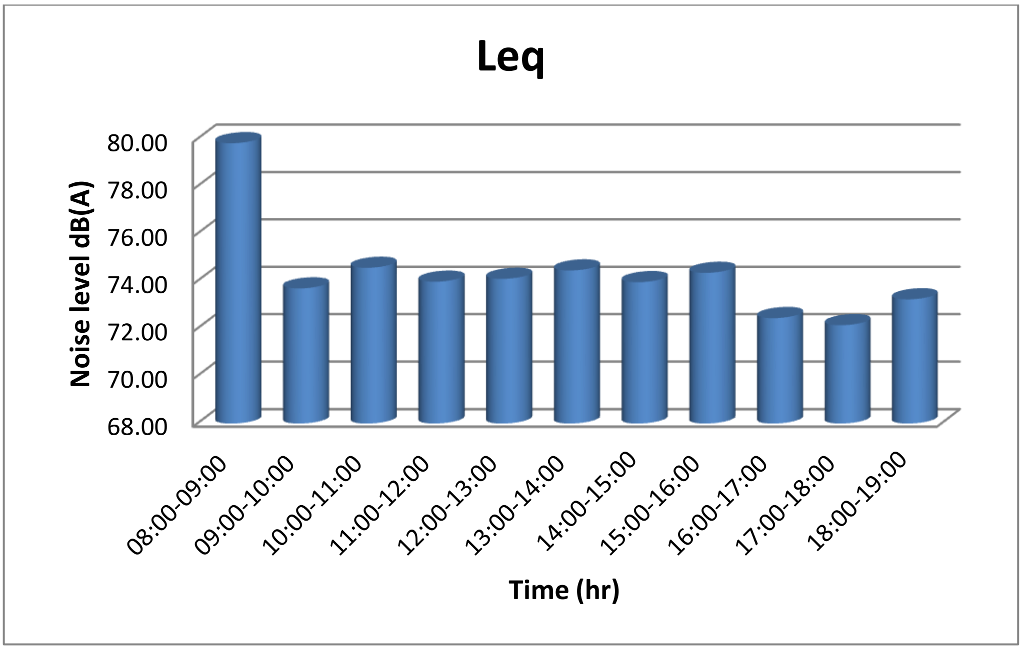

Figure 3.6: Temporal variation of Leq at Punjabi bagh

Table 3.5 : Leq peak, L10, L50, L90 measured at Punjabi bagh

Time	Leq peak	L10	L50	L90
08:00-09:00	101	82	78	76
09:00-10:00	93	76	73	70
10:00-11:00	96	77	73	71
11:00-12:00	94	76	73	71
12:00-13:00	94	76	73	71
13:00-14:00	95	77	73	71
14:00-15:00	96	76	73	70
15:00-16:00	96	77	73	70
16:00-17:00	93	75	71	69
17:00-18:00	91	74	71	69
18:00-19:00	92	75	72	70

- **Data collection at Janpath:-**
  Data collected at Janpath is been shown below in Figure 3.7 and in the Table 3.6.

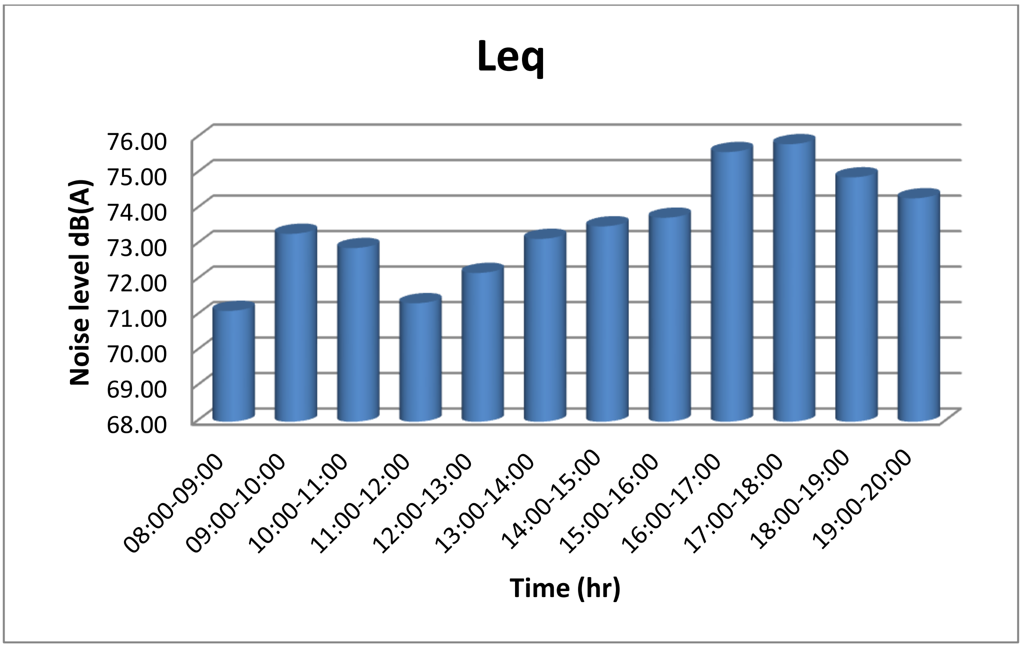

Figure 3.7: Temporal variation of Leq at Janpath

Table 3.6 : Leq peak, L10, L50, L90 measured at Janpath

Time	Leq peak	L10	L50	L90
08:00-09:00	95	73	69	66
09:00-10:00	97	76	71	68
10:00-11:00	97	74	70	67
11:00-12:00	95	73	69	66
12:00-13:00	96	75	70	67
13:00-14:00	98	75	70	68
14:00-15:00	98	75	71	68
15:00-16:00	97	76	71	69
16:00-17:00	102	78	72	69
17:00-18:00	102	78	72	69
18:00-19:00	99	77	72	70
19:00-20:00	99	76	72	69

❖ **Data collection at Madhuban Chowk:-**

Data collected at Madhuban Chowk is been shown below in Figure 3.8 and in the Table 3.7.

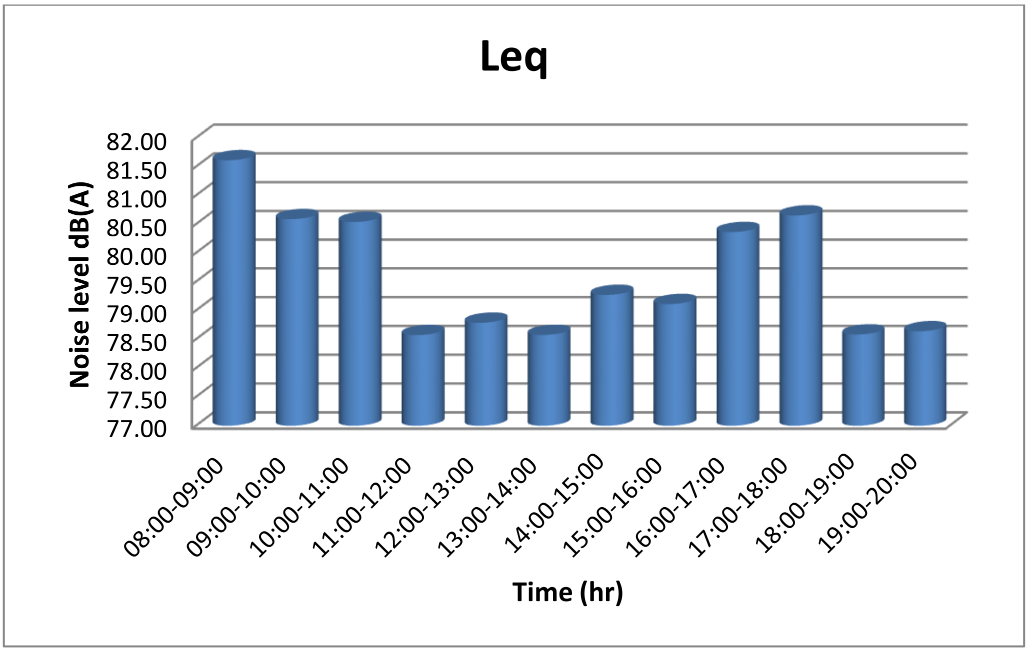

Figure 3.8: Temporal variation of Leq at Madhuban Chowk

Table 3.7 : Leq peak, L10, L50, L90 measured at Madhuban Chowk

Time	Leq peak	L10	L50	L90
08:00-09:00	84	79	75	105
09:00-10:00	83	78	75	103
10:00-11:00	83	78	75	103
11:00-12:00	81	77	74	100
12:00-13:00	81	77	75	100
13:00-14:00	81	76	74	101
14:00-15:00	82	76	73	104
15:00-16:00	81	77	74	102
16:00-17:00	83	78	74	103
17:00-18:00	83	78	75	102
18:00-19:00	81	77	74	100
19:00-20:00	81	77	74	100

Chapter 4:- MODELLING OF NOISE POLLUTION

4.1 General.

MATLAB was used to built neural networks to predict the noise level (Leq) at six identified locations. Various networks were created by varying the following parameters:-

1. Number of hidden layers
2. Number of Neurons
3. Transfer function
4. Maximum number of epochs upto which training is to be carried out.

The results obtained from each of the networks are given below.

4.2 Artificial Neural network for noise level prediction

We have used feed forward Backpropagation network type as it is a systematic method for training multi-layer artificial neural network. The method of gradient was Levenberg. The neural network is been built with MATLAB, which has multiple functions for data processing with neural networks. The structure of this neural network in MATLAB is shown in the Figure 4.1.

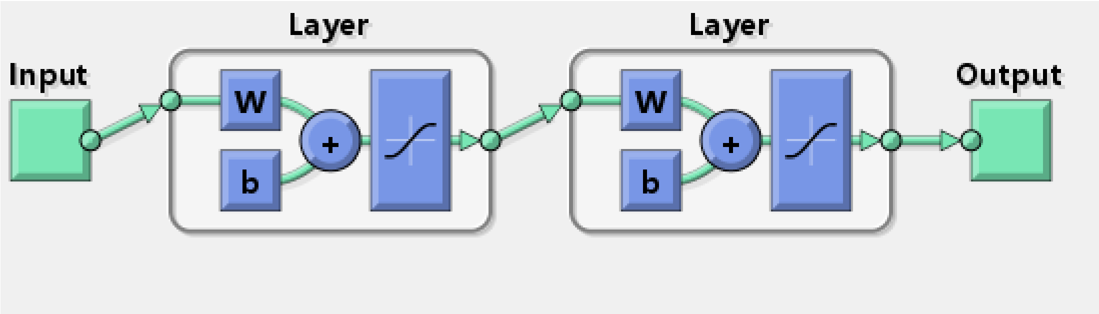

Figure 4.1: Structure of the proposed neural network.

The road traffic noise was calculated in the batch experiments as a function of volume of the traffic, speed of the traffic, number of heavy vehicles and the road traffic noise. ANN model based on single layer recurrent back propagation algorithm for the data, generated from the above experiments was applied to train the Neural Network. During training, the output is computed by a forward pass in which the input is propagated forward through the network to compute the output value of each unit. The output is then compared with the desired values which results with few errors to each output unit. In order to minimize the errors, suitable adjustments were made for each of the weights of the network. And after several such iterations, network was trained to give the desired output for a given input values. The single layer network structure included six hidden neurons, describing the dynamics of road traffic noise is shown in the Fig.4.2. And the performance of network simulation was evaluated in terms of mean square error (MSE) criterion. The MSE for the training and cross validation data sets were found to be at desired accuracy.

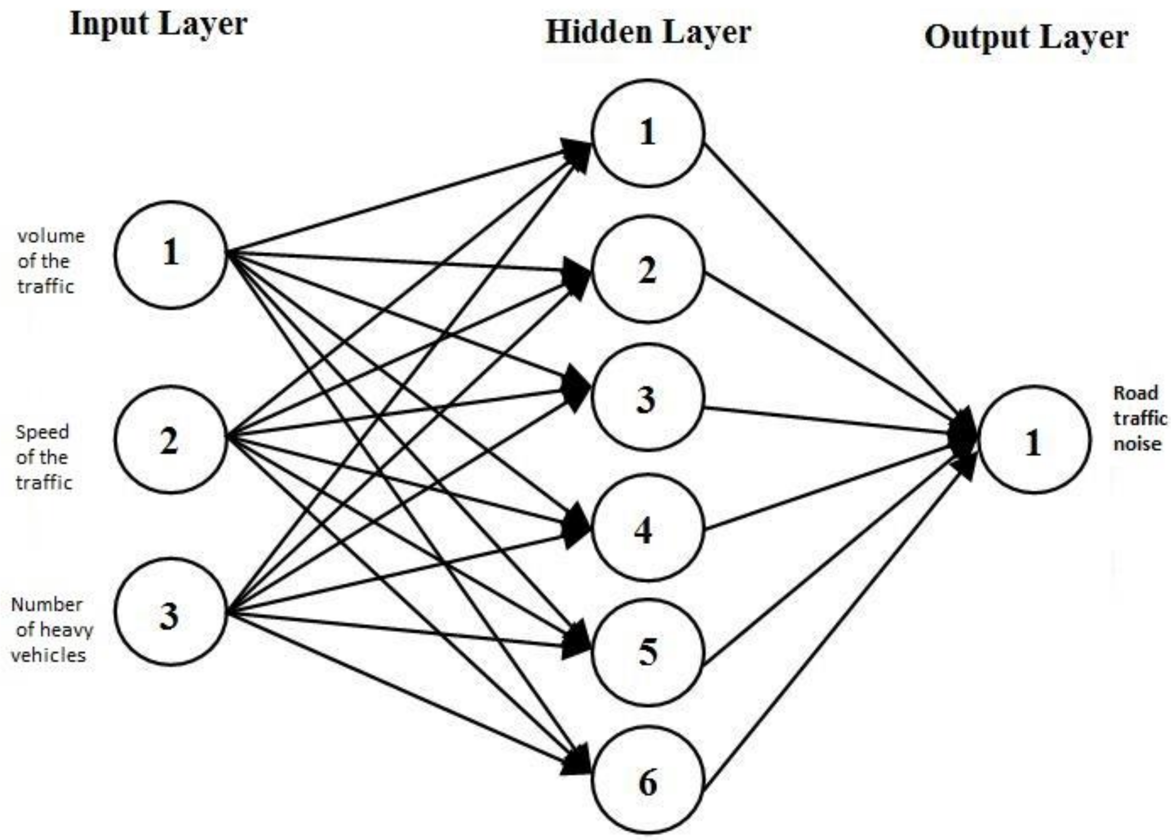

Figure 4.2: ANN model single layer noise prediction.

4.3 Data Parameters.

4.3.1 **Input.** Each of the site networks were formed with the following inputs.

i. Classified traffic Volume.

ii. Classified Traffic speed.

4.3.2 **Output**. Output in all networks was Leq.

4.3.3 **Data Distribution.** The details of all the locations, the total data sets in the zone and the division of the total data sets into training, cross validation and testing data sets is given in Table 4.1.

Table 4.1: List of complete data parameters used in ANN model.

Locations	1,2,3,4,5,6
Total No of Data sets	66
Training sets	54 (81%)
Testing Sets	12 (18%)

4.4 Network Details.

4.4.1 Networks with Classified Traffic Volume as Input.

The following inputs were considered in these networks:-

1. Hourly volume of car/jeep/van of both the sides of roads.
2. Hourly volume of three wheeler of both the sides of roads.
3. Hourly volume of scooter/ motor cycle of both the sides of roads.
4. Hourly volume of Mini bus/ bus of both the sides of roads.
5. Hourly volume of Mini truck/ truck of both the sides of roads.

The Traffic volume of both the sides was considered. The number of inputs was ten, five on each side. The number of obtained output was only one, i.e. Leq. The details of all the networks made in each location and the Mean square error (MSE), Mean Absolute Error (MAE), coefficient of correlation (*r)* are given in Table 4.2. The final mean square error is the one obtained after the network stops training based on the specified termination criterion.

Table 4.2: Details of all selected location Networks with Classified Traffic Volume as Input.

Trial No	Train 1	Train 2	Train 3	Train 4	Train 5	Train 6	Train 7	Train 8
No. of hidden layers	1	1	1	1	1	1	1	1
Number of hidden neurons	3	4	5	6	7	8	9	10
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Number of epochs	13	11	9	10	11	7	24	10
Learning	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg
MSE	0.0371	0.0305	0.0273	0.0260	0.0819	0.0357	0.0473	0.04319
MAE	0.0168	0.0187	0.0243	0.0154	0.0268	0.0162	0.0189	0.02295
r	0.838816	0.86037	0.754848	0.87042	0.819903	0.816697	0.849937	0.85354

Notes: MSE – Mean Square Error; MAE – Mean Absolute Error; *r* – coefficient of correlation.

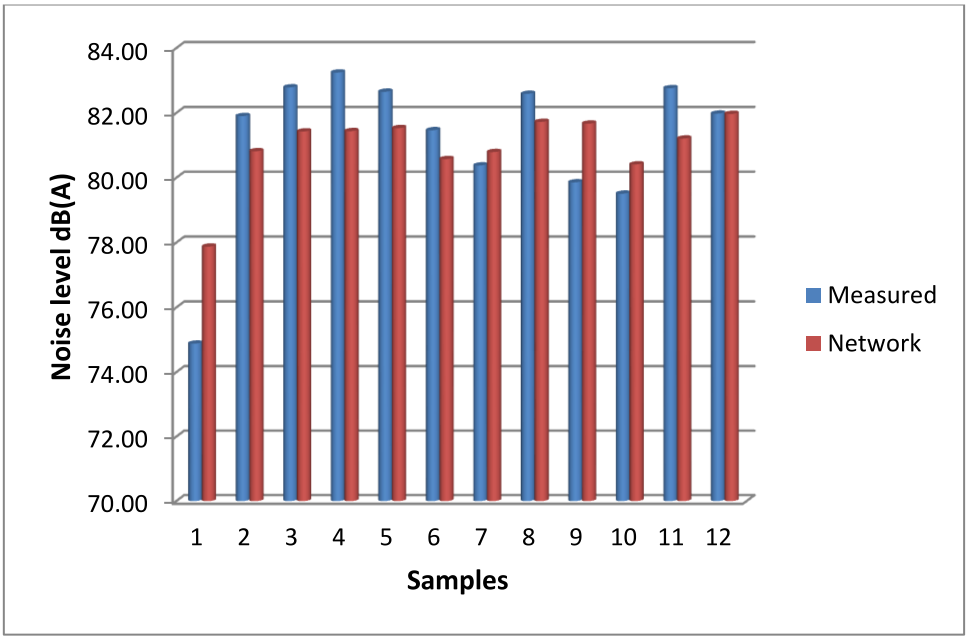

Figure 4.3: Measured and predicted noise levels of network by using ANN model

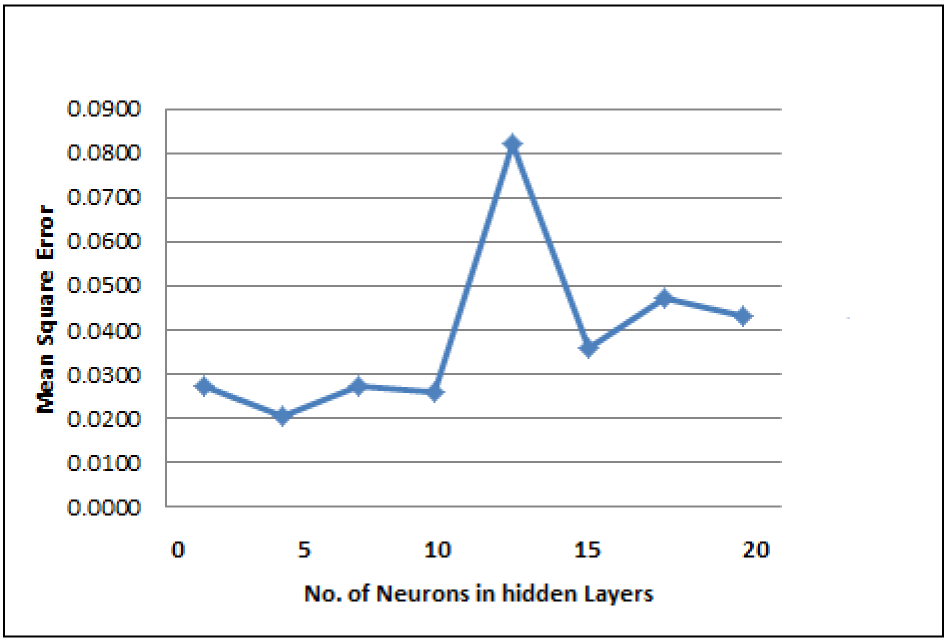

Figure 4.4: Variation of MSE with no. of hidden Layer Neurons.

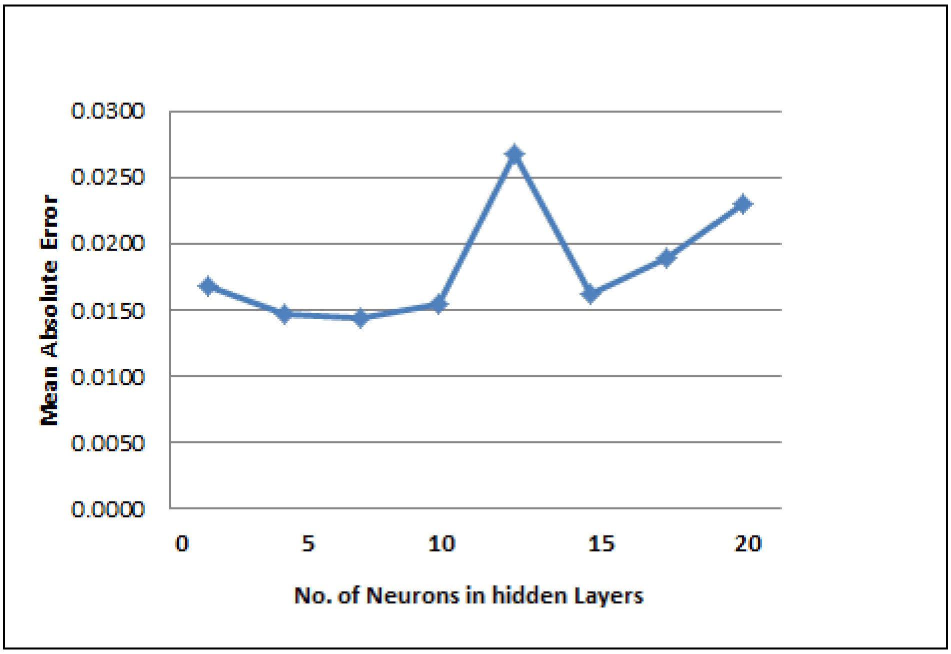

Figure 4.5 : Variation of MAE with no. of hidden Layer Neurons.

4.4.2 Networks with Classified Traffic Volume and Classified traffic Speed as Input.

The following inputs were considered in these networks:-

1. Hourly volume of car/jeep/van of both the sides of roads.
2. Hourly volume of three wheeler of both the sides of roads.
3. Hourly volume of scooter/ motor cycle of both the sides of roads.
4. Hourly volume of Mini bus/ bus of both the sides of roads.
5. Hourly volume of Mini truck/ truck of both the sides of roads.
6. Average hourly spot speed of car/jeep/van of both the sides of roads.
7. Average hourly spot speed of three wheeler of both the sides of roads.
8. Average hourly spot speed of scooter/ motor cycle of both the sides of roads.
9. Average hourly spot speed of Mini bus/ bus of both the sides of roads.
10. Average hourly spot speed of Mini truck/ truck of both the sides of roads.

The Traffic volume of both the sides was considered. The number of inputs was twenty, ten on each case. The number of obtained output was only one, i.e. Leq. The details of all the networks made in each location and the Mean square error (MSE), Mean Absolute Error (MAE), coefficient of correlation (*r*) are given in Table 4.3. The final mean square error is the one obtained after the network stops training based on the specified termination criterion.

Table 4.3: : Details of all selected location Networks with Classified Traffic Volume and Classified traffic Speed as Input.

Trial No	Train 1	Train 2	Train 3	Train 4	Train 5	Train 6	Train 7	Train 8	Train 9
No. of hidden layers	1	1	1	1	1	1	1	1	1
Number of hidden neurons	3	4	5	6	7	8	9	10	11
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Number of epochs	6	6	9	11	7	6	6	11	8
Learning	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg	Levenberg
MSE	0.03349	0.04036	0.04342	0.05716	0.03500	0.04268	0.03935	0.03946	0.03503
MAE	0.01709	0.01845	0.02536	0.02525	0.02320	0.02227	0.01857	0.02288	0.01849
r	0.892792	0.757996	0.819661	0.829879	0.85949	0.87959	0.847829	0.883784	0.843735

Note: MSE – Mean Square Error; MAE – Mean Absolute Error; *r* – coefficient of correlation.

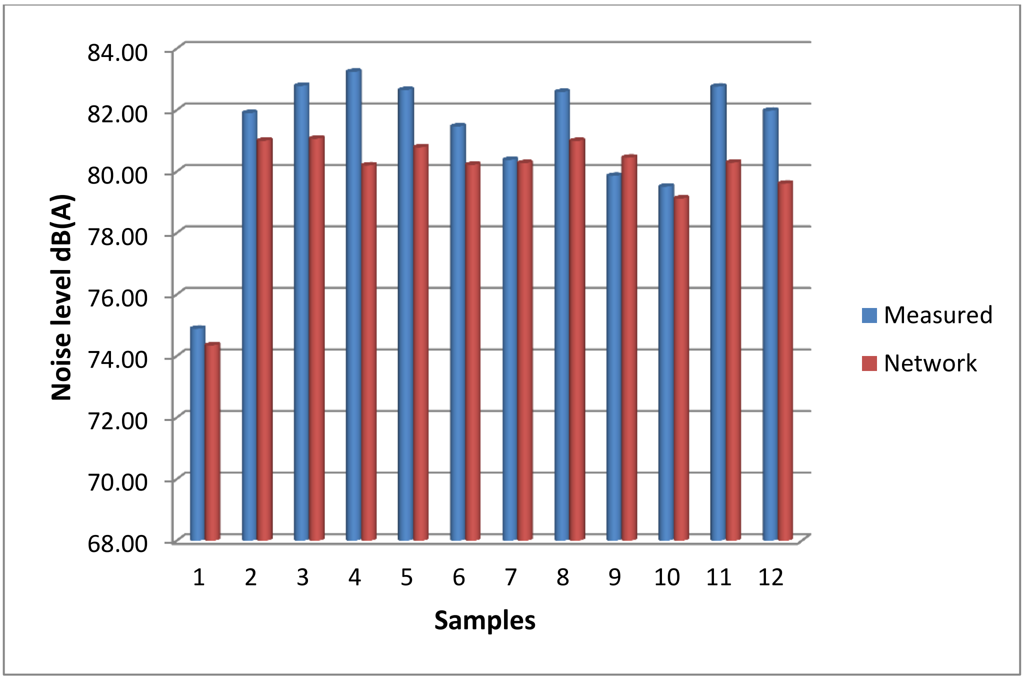

Figure 4.6: Observed and predicted noise levels of best network using ANN model

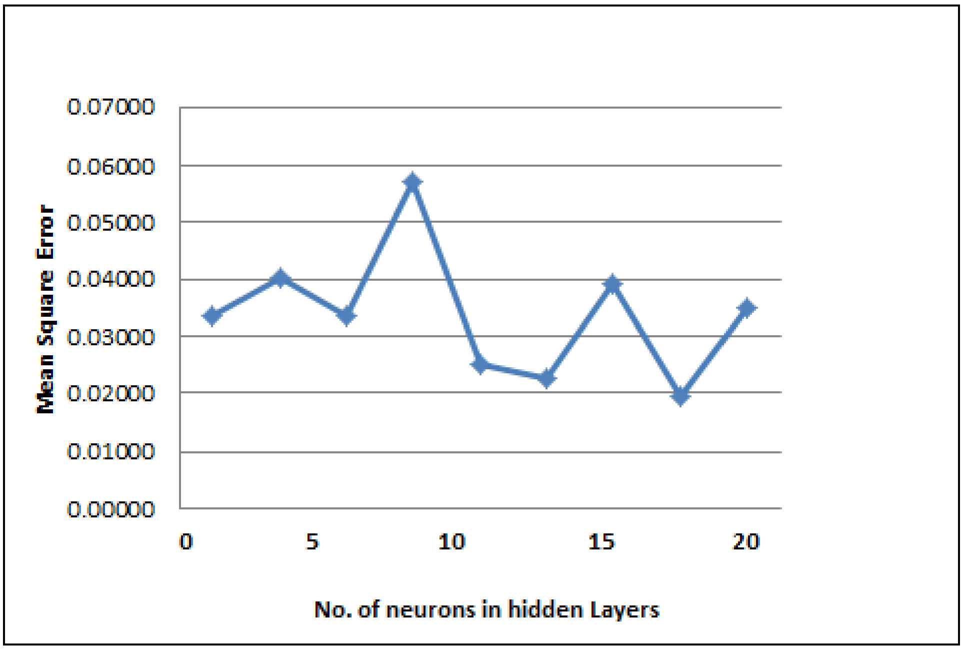

Figure 4.7: Variation of MSE with no. of hidden Layer Neurons.

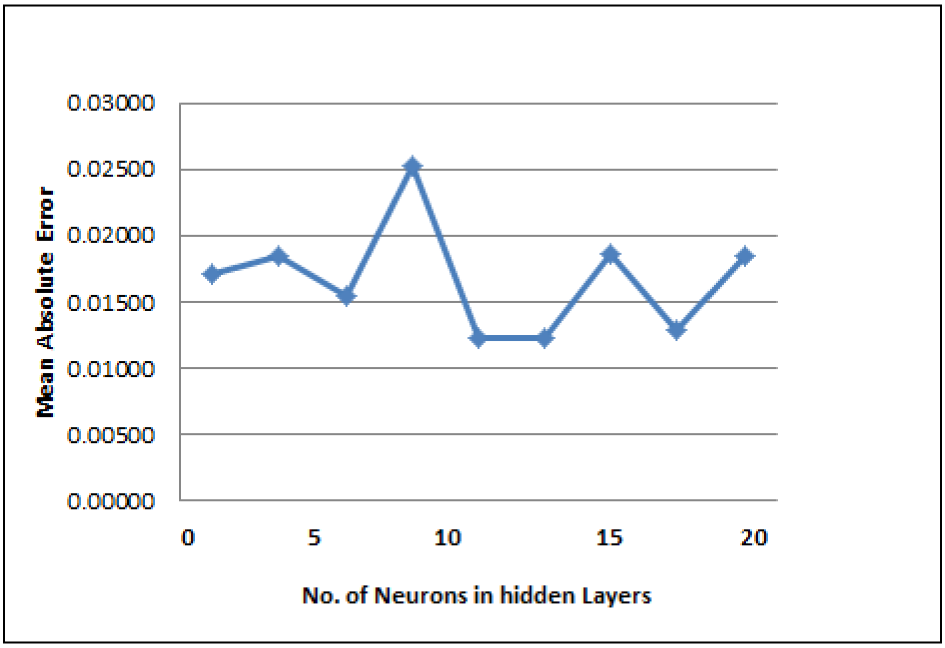

Figure 4.8: Variation of MAE with no. of hidden Layer Neurons.

The networks formed are able to show good results when both the classified traffic volume and classified speed were considered. It is been observed from the above that different land use pattern has a different effect on the traffic noise generated with the same inputs. this would be due to the different characteristics of traffic passing through different areas. The prediction in heavy traffic zone was not satisfactory. The unsatisfactory prediction in heavy traffic zones may be due to the additional sound being generated by Stop and Go traffic and by honking of horns in such congested areas.

The network 1 with 3 number of hidden neurons shows the best result for the coefficient of correlation (0.89279) in case when both the classified traffic volume and the classified traffic speed were considered. Whereas the values in the case when only classified traffic volume was taken as an input were not upto the standards of the values resulted from network when both the traffic volume and the traffic speed were taken as an input.

It is clear that the networks were able to produce better results when both classified speed and classified traffic volume were used as input instead of classified volume alone, thus indicating that speed of each category of vehicles plays a significant role on noise.

Chapter 5:- CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

Following conclusions can be drawn from the above study:-

I. In case of classified traffic volume and classified speed the best results was of network 1 with 3 number of hidden neurons: with 6 epochs. The value of *r* was 0.89279 and MSE was 0.03349.

II. In case of classified volume input the best result was of network 4 with 6 number of hidden neurons: with 10 epochs. The *r* value was found to be 0.87042 and MSE value was 0.0260.

III. It has been observed that different locations have different effects on the traffic noise generated as shown in the results with the same inputs in each locations. It is also clear that the results obtained in case when both classified traffic volume and classified traffic speed were used as a input were better then the results of only classified traffic volume alone.

IV. Percentage of heavy vehicles, speed of heavy vehicles and traffic flow are identified as prominent factor and play significant role in traffic noise emission and therefore environmental impact on public health. Moreover current study reveals that road transportation noise prediction model can be used to reduce the traffic noise level by designing noise absorbent systems on the basis of noise prediction.

5.2 Recommendations.

Data collection for a much longer period is recommended for developing a model which can provide reasonable accuracy to predict the pollution in any area.

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Appendix A

Classified Traffic volume data for all the identified locations.

Classified Traffic volume of Laxmi nagar

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	4456	4552	410	16	1376
09:00-10:00	4728	5944	680	21	1450
10:00-11:00	3218	4492	546	10	1618
11:00-12:00	3106	3658	552	47	1910
12:00-13:00	3152	3654	652	22	2110
13:00-14:00	3360	3766	424	26	1330
14:00-15:00	2800	3524	440	31	1646
15:00-16:00	3404	3826	668	40	2082
16:00-17:00	3156	3518	604	42	1530
17:00-18:00	3160	3702	346	32	1348
18:00-19:00	3208	4624	374	17	1512
19:00-20:00	3538	6244	584	36	1980

Classified Traffic volume of Uttam nagar

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	1250	1790	780	100	750
09:00-10:00	1428	2066	936	104	788
10:00-11:00	1092	1892	564	192	436
11:00-12:00	1160	2284	542	144	600
12:00-13:00	1110	2280	580	136	484
13:00-14:00	1051	2080	628	114	432
14:00-15:00	1310	2532	840	90	704
15:00-16:00	1400	3978	646	92	840
16:00-17:00	960	4184	750	72	652
17:00-18:00	1138	5380	984	102	1076
18:00-19:00	952	3513	828	60	1192
19:00-20:00	1336	4308	644	36	788

Classified Traffic volume of Karol bagh

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	3264	2220	200	12	756
09:00-10:00	3056	2826	162	14	746
10:00-11:00	1924	2520	178	14	800
11:00-12:00	2266	3644	212	10	854
12:00-13:00	2284	3328	195	11	812
13:00-14:00	3120	2276	181	28	830
14:00-15:00	2902	2580	188	10	906
15:00-16:00	2352	2822	177	28	976
16:00-17:00	2258	3564	248	22	984
17:00-18:00	2482	3324	206	10	1576
18:00-19:00	2544	3940	196	13	1284
19:00-20:00	2156	3936	176	9	1548

Classified Traffic volume of Punjabi bagh

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	4762	4338	164	22	700
09:00-10:00	3144	4784	148	26	1032
10:00-11:00	3036	4546	220	42	1644
11:00-12:00	2536	3806	166	280	2320
12:00-13:00	2644	2688	188	226	2250
13:00-14:00	2540	2312	76	376	2192
14:00-15:00	2576	2728	158	206	1938
15:00-16:00	2950	2840	128	184	1736
16:00-17:00	2900	2848	182	194	3180
17:00-18:00	3730	3666	210	66	1802
18:00-19:00	3616	3566	232	32	1336
19:00-20:00	3776	3600	210	46	1458

Classified Traffic volume of Janpath

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	870	340	45	22	480
09:00-10:00	1132	322	50	18	540
10:00-11:00	1786	432	48	20	548
11:00-12:00	1752	564	64	8	692
12:00-13:00	2154	408	44	16	512
13:00-14:00	2296	572	24	17	724
14:00-15:00	1748	698	28	8	428
15:00-16:00	1516	572	20	14	388
16:00-17:00	1432	632	20	12	720
17:00-18:00	1688	782	14	8	960
18:00-19:00	1676	740	26	12	832
19:00-20:00	1616	440	22	14	820

Classified Traffic volume of Madhuban chowk

Time	Both side volume				
	C/J/V	S/M	B	T	TW
08:00-09:00	2600	2000	144	30	240
09:00-10:00	2400	1880	136	16	268
10:00-11:00	3132	2800	156	4	156
11:00-12:00	2880	2680	148	144	832
12:00-13:00	3120	2040	192	104	604
13:00-14:00	3080	2160	140	36	396
14:00-15:00	3320	1720	272	84	588
15:00-16:00	3160	1880	296	96	824
16:00-17:00	2880	1520	340	120	908
17:00-18:00	2928	1760	224	40	776
18:00-19:00	2952	1400	176	28	576
19:00-20:00	3060	1920	160	24	776

Appendix B

The spot speed data for all the identified locations.

The spot speed data at Laxmi nagar

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	44	53	41	43	42
09:00-10:00	40	49	39	37	46
10:00-11:00	42	44	42	39	46
11:00-12:00	41	45	42	39	44
12:00-13:00	41	47	39	41	47
13:00-14:00	42	48	38	41	41
14:00-15:00	42	44	36	42	45
15:00-16:00	43	49	41	40	45
16:00-17:00	44	47	37	37	42
17:00-18:00	45	51	37	37	39
18:00-19:00	49	53	39	39	41
19:00-20:00	38	49	38	41	43

The spot speed data at Uttam nagar

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	57	54	41	38	46
09:00-10:00	55	51	38	40	44
10:00-11:00	54	50	39	41	47
11:00-12:00	51	53	39	36	45
12:00-13:00	43	47	40	35	45
13:00-14:00	46	46	42	39	46
14:00-15:00	48	49	40	39	48
15:00-16:00	49	45	37	41	40
16:00-17:00	54	55	35	41	42
17:00-18:00	46	51	32	40	42
18:00-19:00	42	56	33	35	43
19:00-20:00	44	51	34	37	45

The spot speed data at Karol bagh

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	45	43	40	41	43
09:00-10:00	40	42	38	36	34
10:00-11:00	40	43	36	36	35
11:00-12:00	42	45	34	37	35
12:00-13:00	44	40	38	35	33
13:00-14:00	41	39	32	35	32
14:00-15:00	46	45	39	38	39
15:00-16:00	47	50	39	39	40
16:00-17:00	48	50	36	36	42
17:00-18:00	52	51	41	39	45
18:00-19:00	49	50	40	39	44
19:00-20:00	48	51	39	38	46

The spot speed data at Punjabi bagh

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	48	50	39	36	40
09:00-10:00	49	48	38	33	41
10:00-11:00	32	31	34	29	37
11:00-12:00	36	38	36	33	40
12:00-13:00	36	38	35	27	39
13:00-14:00	35	37	33	31	40
14:00-15:00	36	39	32	32	41
15:00-16:00	38	40	33	36	39
16:00-17:00	33	35	36	29	38
17:00-18:00	31	34	31	30	33
18:00-19:00	34	37	38	37	32
19:00-20:00	35	38	32	37	31

The spot speed data at Janpath

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	38	41	36	38	36
09:00-10:00	32	35	32	33	32
10:00-11:00	33	37	33	32	32
11:00-12:00	34	35	33	32	34
12:00-13:00	34	39	31	31	33
13:00-14:00	36	37	29	28	31
14:00-15:00	37	40	28	36	36
15:00-16:00	35	38	29	36	35
16:00-17:00	36	42	31	35	37
17:00-18:00	38	45	35	37	35
18:00-19:00	40	41	36	35	37
19:00-20:00	37	41	35	31	33

The spot speed data at Madhuban chowk

Time	Both side volume				
	SCJV	SSM	SB	ST	STW
08:00-09:00	52	47	40	41	45
09:00-10:00	45	47	41	37	47
10:00-11:00	42	41	38	39	47
11:00-12:00	46	42	38	37	44
12:00-13:00	48	46	37	35	45
13:00-14:00	42	39	36	36	39
14:00-15:00	38	41	36	36	38
15:00-16:00	39	42	38	37	39
16:00-17:00	38	45	40	38	39
17:00-18:00	52	51	40	38	40
18:00-19:00	51	53	39	38	40
19:00-20:00	36	41	35	35	43

Appendix C

The Meterological data for all the identified locations.

Location	Date of Survey	Temperature (°C)	Humidity (%)	Wind speed (km/hr)	Wind direction
Madhuban chowk	**08-04-2015**	31	37	8	N
Laxmi Nagar	**10-04-2015**	33	40	13	WNW
Karol Bagh	**16-04-2015**	29	54	5	SE
Punjabi Bagh	**24-04-2015**	38	18	8	WNW
Uttam Nagar	**01-05-2015**	39	18	8	WNW
Janpath	**04-05-2015**	29	37	14	ENE