TRAFFIC NOISE MODELLING USING

ARTIFICIAL NEURAL NETWORK

A Thesis

Submitted in partial fulfillment of the requirement for the award of

degree of

MASTER'S OF ENGINEERING

IN

PRODUCTION AND INDUSTRIAL ENGINEERING

Submitted By

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CERTIFICATE

I hereby certify that the work which is being presented in this thesis entitled **"TRAFFIC NOISE MODELLING USING ARTIFICIAL NEURAL NETWORK"** inpartial fulfilment of requirement for the award of **Master's Degree in Production & Industrial Engineering** submitted in Mechanical Engineering Department, Thapar University, Patiala, is an authentic record of the work carried out by me under the guidance **of Dr.S.P Nigam, Visiting Professor** and **Mr.Daljeet Singh, Assistant Professor, Mechanical Engineering Department, Thapar University, Patiala.**

The matter embodied in this report has not been submitted in part or full to any other university or institute for the award of any degree.

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ABSTRACT

Highway traffic noise has been a federal, state, and local problem. Emanating from vehicle engines, exhaust systems, and tires interacting with pavement, traffic noise affects the quality of life for nearby residents and businesses by drowning out conversations, disrupting sleep, and discouraging outdoor activities. Over the years, community and motorist concerns have fueled the push to improve noise measurement and modeling tools that help transportation agencies address the highway traffic noise problem.

The heterogeneous features of traffic noise, together with the characteristics of environmental noise, with their great spatial, temporal and spectral variability, makes the matter of modeling and prediction a very complex and non-linear problem, therefore a need is being felt to develop a traffic noise prediction model suitable for the Indian condition.

The present work represents a traffic noise prediction model taking Patiala-Sangrur highway as a representative/demonstrative site. All the measurements of noise levels were measured at selected points around the highway at different time intervals on number of days in a random/staggered manner in order to account for statistical temporal variations in traffic flow conditions.

The noise measurement parameters recorded are Traffic volume and Average speed of vehicles and the noise descriptors recorded are Equivalent Noise Level (Leq), Percentile Noise Level (L_{10}), Maximum Equivalent Noise Level (L_{MAX}) and Minimum Equivalent Noise Level (L_{MIN}). Effects of noise parameters on noise descriptors were also studied.

Artificial Neural Network (ANN) approach has been applied for traffic noise modeling in the present study. The measured parameters were divided into two classes i.e. output parameters (L_{10}, L_{eq}) and input parameters (vehicle volume/hr., percentage of heavy vehicles and average vehicle speed). The input parameters are further divided randomly into three kinds of samples

- **Training set**
- **Validation set**
- **Testing set**

After training and testing of the ANN, it was found that the values of correlation coefficient(R) were 0.9434, 0.9644 & 0.92863 for the training, validation and testing samples respectively, and

the percentage error varied from -0.19 to 0.64 and 0.54 to 0.99 for Leq and L10, therefore a good correlation coefficient and less percentage error between experimental and predicted output is an indication of better prediction capability of neural network.

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NOMENCLATURE

SYMBOL	DESCRIPTION
L_w	Sound Power Level in Decibel (dB)
LI	Sound Intensity Level (dB)
L_p	Sound Pressure Level (dB)
L_{eq}	Equivalent Sound Level (dB)
L_X	Percentile Exceeded Sound Level
L_{dn}	Day Night Average Sound level
TNI	Traffic Noise Index
NPL	Noise Pollution Level
ANN	Artificial neural Network
BP	Back propagation

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Sound is defined as any pressure variation that the ear can detect ranging from the weakest sounds to sound levels which can damage hearing.

The study of sound is called acoustics and covers all fields of sound Production, sound propagation and sound reception, whether created and received by human beings or by machines and measuring instruments.

Sound can be classified as two types based on its use to mankind.

- Sound that is useful to mankind like music, speech which we use for communication.
- Sound that is not useful to mankind like the sound from an aircraft, bursting of high intensity crackers, blaring sound speakers etc. this is called Noise.

The word noise is derived from the Latin term **nausea.** It has been defined as unwanted sound, a potential hazard to health and communication dumped into the environment with regard to the adverse effect it may have on unwilling ears.

Noise is defined as unwanted sound. Sound, which pleases the listeners, is music and that which causes pain and annoyance is noise.

1.2 PHYSICAL PROPERTIES OF SOUND

1.2.1 The Decibel [46]

Decibel is a logarithmic unit used to describe physical values like the ratio of the signal level - power, sound pressure, voltage or intensity.

The decibel can be expressed as:

$$\text{Decibel} = 10 \log_{10}(P / P_{ref})$$

Where

P = sound power (W)

P_{ref} = reference power (W)

Decibel addition

Decibel levels are added logarithmically and not algebraically. For example, 70 dB plus 70 dB does not equal 140 dB, but only 73 dB. A very simple, but usually adequate, schedule for obtaining the sum of two decibel values is:

When two decibel values differ by	**Add the following amount to the higher value**
0 or 1 dB	3dB
2 or 3 dB	2dB
4 or 9 dB	1dB
10 dB or more	0dB

Table-1 Decibel Addition

When several decibel values are to be added, following equation should be used

$$L_{sum} = 10 \log_{10} [10^{Lp1/10} + 10^{Lp2/10} +\ldots\ldots + 10^{Lpn/10}]$$

In the special case where decibel levels of equal magnitudes are to be added, the cumulative level can be determined with equation given below:

$$L_{sum} = L_p + 10 \log_{10} (n)$$

Where n is the number of sources, all with magnitude Lp.

1.2.2 Sound power level

Sound power is the energy rate - the energy of sound per unit of time (J/s, W in SI-units) from a sound source.

Sound power can more practically be expressed as a relation to the threshold of hearing - 10^{-12} W - in a logarithmic scale named Sound Power Level –L_w:

$$L_w = 10 \log_{10} (P / P_{ref})$$

Where
L_w = Sound Power Level in Decibel (dB)
P = sound power (W)

- The lowest sound level that people of excellent hearing can discern has an acoustic sound power about 10^{-12} W, 0 dB
- The loudest sound generally encountered is that of a jet aircraft with a sound power of 10^5 W, 170 dB.

1.2.3 Sound Intensity

Sound Intensity is the Acoustic or Sound Power (W) per unit area. The SI-units for Sound Intensity are W/m^2.

The Sound Intensity Level can be expressed as:

$$LI = 10 \log_{10} (I / Iref)$$

where
LI = sound intensity level (dB)
I = sound intensity (W/m^2)
Iref = 10^{-12} - reference sound intensity (W/m^2)

1.2.4 Sound Pressure Level

The Sound Pressure is the force (N) of sound on a surface area (m^2) perpendicular to the direction of the sound. The SI-units for the Sound Pressure are N/m^2 or Pa.

The Sound Pressure Level:

$$L_p = 10 \log_{10}(p^2 / p_{ref}^2) = 10 \log_{10}(p / p_{ref})^2 = 20 \log_{10}(p / p_{ref})$$

Where

L_p = sound pressure level (dB)

p = sound pressure (Pa)

$p_{ref} = 2 \times 10^{-5}$ - reference sound pressure (Pa)

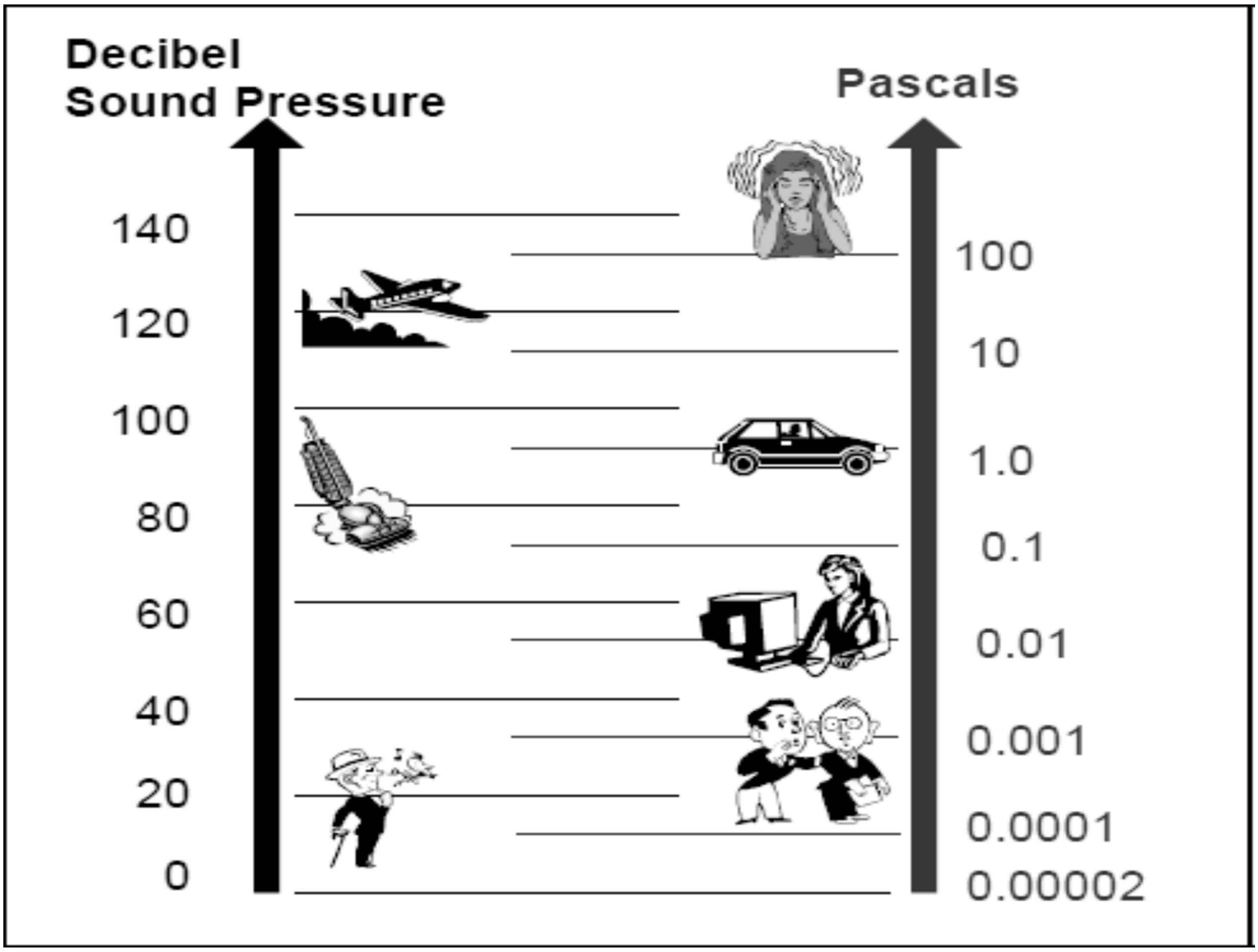

FIG.1 Typical Sound Pressure Levels (Application Guide AG 31-010-acoustics fundamental)

The effect of converting from pressure units to decibels, note that doubling any value of sound pressure results in an increase in the sound pressure level of 6 dB.

If the sound pressure is increased by a factor of 10 the sound pressure level only increases by 20 dB. This can also be shown by above representation.

1.3 SOUND SOURCES

Sound intensity decreases in proportion with the square of the distance from the source. Sound levels for a highway line source vary differently with distance, because sound pressure waves propagate along the line and overlap at the point of measurement. A long, closely spaced, continuous line of vehicles along a roadway becomes a line source. The several sound sources are as follows:

- Point Source
- Line Source
- Plane Source

1.3.1 Sound from a Point Source

As soon as sound energy is released from a source, it interacts with the environment and creates sound pressure in a source – path – receiver arrangement. The most fundamental example is a point sound source emanating energy uniformly in all directions. Sound waves will travel uniformly in a spherical manner from a point sound source. The sound pressure level will decrease as a function of distance as follows,

$$Lp = Lw + 10\text{Log}\,(Q/4\pi d^2) + k$$

Where

D= is the distance in feet (m) from the source to the measurement point

Q= is the directivity factor, which for spherical radiation is 1

k =is a constant whose value is 0.5 for SI units

Ideally, this works out to a 6 dB drop in sound levels for every doubling of distance.

1.3.2 Sound from a Line Source

A line source is a collection of point sources that radiate sound in a cylindrical pattern. The equation that relates line sound power to sound pressure is,

$$Lp = Lw + 10\text{Log}\,(Q/\pi dL) + k$$

Where

d is the distance from the source to the measurement point

L is the length of the sound source in meters.

K is a constant whose value is 0.5 for SI units

A line source produces a 3 dB (A) decrease in sound level for each doubling of distance

1.3.3 Sound from a Plane Source

A plane source is a surface that radiates sound into a space. In close proximity to the wall, the sound level does not change; making plane sound sources an issue to attenuate. The equations that relate sound power from a plane source to sound pressure are;

When $d < b/\pi$

$$Lp = Lw + 10Log(\pi / (4bc)) + k$$

When $b/\pi < d < c/\pi$

$$Lp = Lw - 10Log(d) - 10Log(4c) + k$$

When $d > c/\pi$

$$Lp = Lw - 20Log(d) - 11 + k$$

Where

d is the distance from the source to the measurement point

c is the larger dimension of the wall in meters.

b is the shorter dimension of the wall in meters.

k is a constant whose value is 0.5 for SI units

1.4 SOUND PROPAGATION

1.4.1 Propagation: Sound (or noise) is the result of pressure variations, or oscillations, in an elastic medium (e.g., air, water, solids), generated by a sound source. Sound propagates in the form of longitudinal waves, involving a succession of compressions and rarefactions in the elastic medium. When a sound wave propagates in air (medium considered), the Oscillations in pressure are above and below the ambient atmospheric pressure.

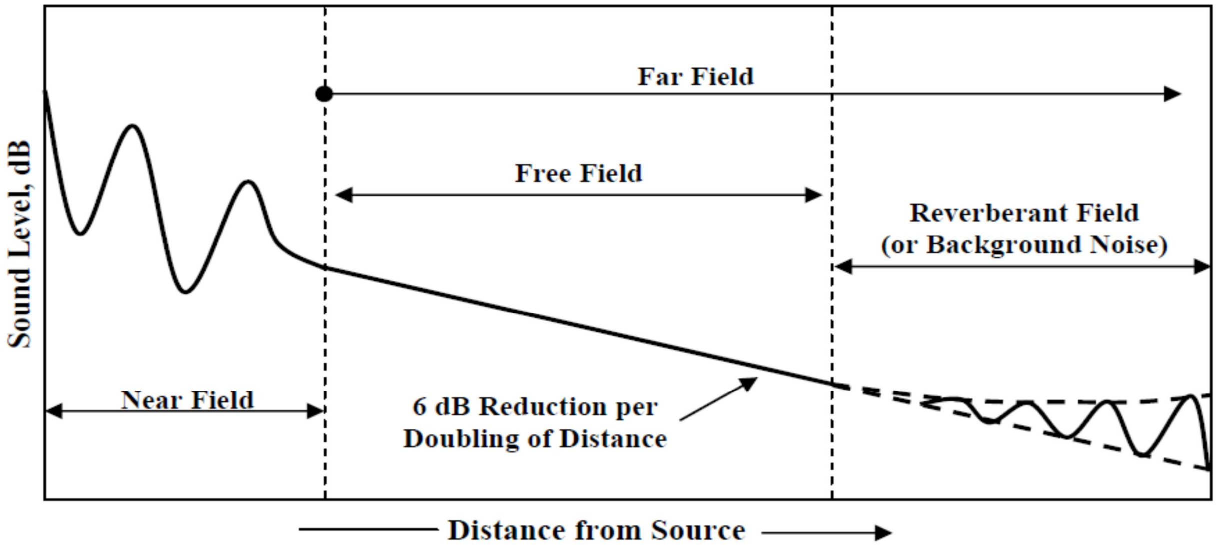

FIG.2 Sound fields [47]

1.4.2 Sound fields

1.4.2.1 Free field

The free field is a region in space where sound may propagate free from any form of obstruction.

1.4.2.2 Near field

The near field of a source is the region close to a source where the sound pressure and acoustic particle velocities are not in phase. In this region the sound field does not decrease by 6 dB each time the distance from the source is increased (as it does in the far field). The near field is limited to a distance from the source equal to about a wavelength of sound or equal to three times the largest dimension of the sound source (whichever is the larger).

1.4.2.3 Far field

The far field of a source begins where the near field ends and extends to infinity. Note that the transition from near to far field is gradual in the transition region. In the far field, the direct field radiated by most machinery sources will decay at the rate of 6 dB each time the distance from the Source is doubled. For line sources such as traffic noise, the decay rate varies between 3 and 4 dB.

1.4.2.4 Direct field

The direct field of a sound source is defined as that part of the sound field which has not suffered any reflection from any room surfaces or obstacles.

1.4.2.5 Reverberant field

The reverberant field of a source is defined as that part of the sound field radiated by a source which has experienced at least one reflection from a boundary of the room or enclosure containing the source.

1.5 BASIC CHARACTERISTICS

1.5.1 Loudness

The definition of loudness levels is as follows: For a given sound, A, the loudness level is defined as the sound pressure level (SPL) of a 1000-Hz tone which is perceived equally loud as sound A. The unit for loudness level is Phon.
In order to measure loudness level a 1 kHz tone is needed and this tone should then be adjusted up and down in level until it is perceived just as loud as the other sound. When this situation is achieved, the sound pressure level of the 1 kHz tone is per definition equal to the loudness level in phon. For a 1000-Hz tone the value in dB SPL and in Phon will be the same.

Phons and Sones

The phon is a non-standard noise unit that is designed to reflect perceived loudness, where sound has to adjust to the decibel level of a reference tone of 1 kHz until it was the same loudness as the signal being measured. So for example, if a sound is 70 phons, that means it sounds as loud as a 70-dB, 1-kHz tone. The dBA scale is now widely used instead of phons.
The sone is another non-standard, psychoacoustic unit of loudness. By definition, 1 sone = 40 phons, and from there upward, the sone measurement doubles for every increase of 10 phons.

Phons	40	50	60	70	80	90	100	110	120
Sones	1	2	4	8	16	32	64	128	256

TABLE.2 [46]

The sone is a more intuitive measure of loudness, because a doubling in the number of sones represents a doubling in perceived loudness (unlike the logarithmic phon scale). Noise levels household fans are often measured in sones.

1.5.2 Threshold of hearing

The response of the human ear to sound or noise depends both on the sound frequency and the sound pressure level. Given sufficient sound pressure level, a healthy, young, normal human ear is able to detect sounds from frequencies 20 Hz to 20,000 Hz.

1.5.3 Loudness Contour

An **equal-loudness contour** is a measure of sound pressure, over the frequency spectrum, for which a listener perceives a constant loudness. The ear does not perceive all sounds equally at the various frequencies or sound intensities. Figure 3 shows an equal loudness contour chart. The sound levels for a particular sound as defined by the level at 1000 Hz will find the same for any given frequency along the curve

For example a 40-decible sound at 1000 Hz would be perceived as the same sound level of 50 decibels at 100 Hz. This indicates that our ears are less sensitive to low frequency sounds than mid to high frequencies

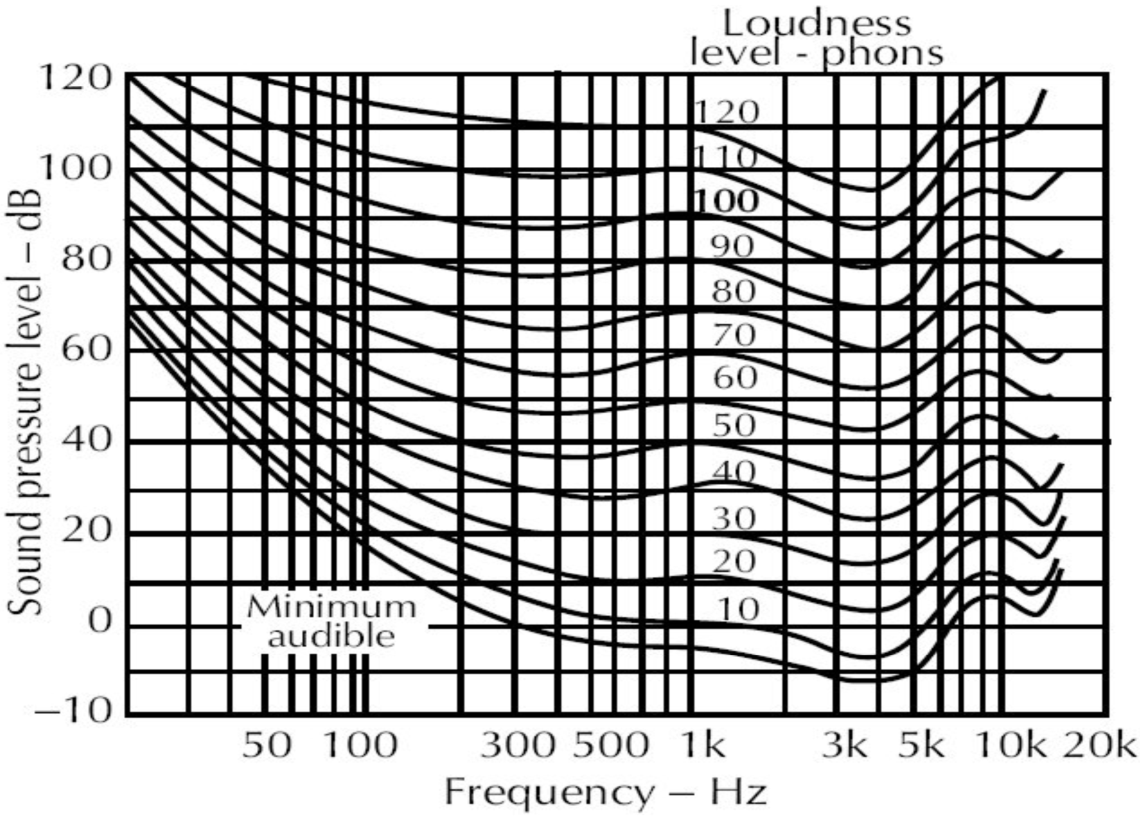

FIG.3 Equal-loudness contour [46]

1.5.4 Weighting curves

The human ear is not equally sensitive to sound at different frequencies. The uneven frequency response of the ear causes a problem when trying to evaluate the annoyance of unwanted sounds, something that often has to be judged. Noise weighting is needed to reflect the fact that the human ear is more sensitive to mid-frequency noise between 1 to 6 kHz than to low and high frequency noise. Any measurement of noise must take due account of human aspects. Measurement devices are equally sensitive to all the frequencies. To encompass the non-uniform behavior of human ear into the measurements weighting networks are generated.

A-Weighted Sound Pressure dB (A)

A-weighted sound pressure is **“**corrected**”** to more closely resemble the hearing characteristics of the human ear. The human ear approximates the A-weighted curve in the 20 to 30 dB range. At these low sound levels, the ear has relatively poor sensitivity to low frequency sound. Table below shows the adjustments for A-weighted sound with the very large adjustments in the lower frequency bands. There is also B and C-weighted sound data, which is meant for louder sound levels. These sound levels are not as common as A-weighted values. An A-weighted sound criterion is most commonly used in outdoor sound evaluations. It is often used in city building codes when referencing the maximum acceptable sound pressure levels at the property line. It is popular because it is a single number that most sound meters include.

Octave Band(Hz)	63	125	250	500	1000	2000	4000	8000
Adjustment dB(A)	-26	-16	-9	-3	0	1	1	-1

Four different response curves are in common use: A, B, C and D

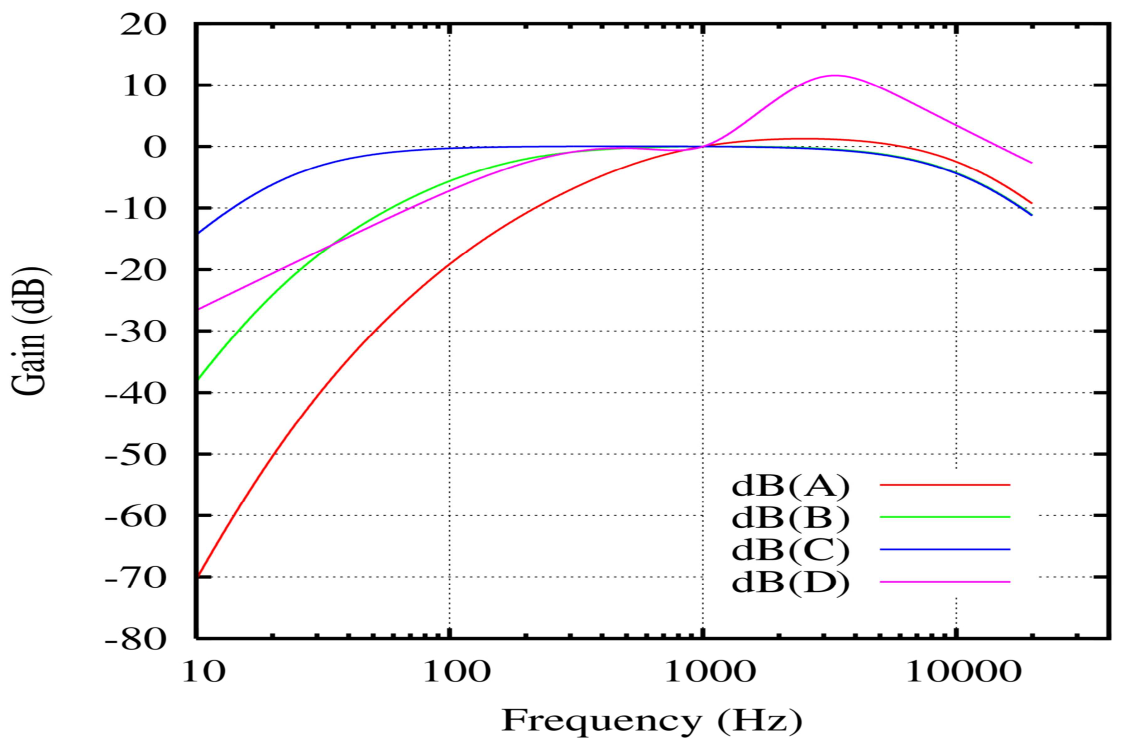

FIG.4 Weighting curves [47]

The A-weighting curve was originally developed to approximate the response of the human ear at low levels. B and C-weighting curves were developed to approximate the response of the human hear at levels of 55-85 dB and above 85 dB, respectively.

1.5.5 Frequency analysis

A single figure A, B, C or D weighted measurement provides a useful indication of noise level, but cannot possibly include all factors which influence the loudness, annoyance and harmfulness of a sound. To take into account the individual tones making up the sound must be investigated by making a frequency analysis. Sound which consist of single frequency is called a pure tone and most generally sounds are distributed over a broad frequency range i.e. a sound wave encompasses different frequencies. For measuring the sound level it is convenient to measure a particular part of the frequency spectrum over which the sound signal is distributed.

For this various filters are used which are having particular bandwidth. These filters measured the sound level as per their frequency bandwidth and rest of the signal is filtered out.

These filters are classified as

1. Constant bandwidth filters (these are independent of the center frequency)
2. Constant percent bandwidth filters (these depend on the center frequency)

Most commonly used constant percent bandwidth filters are 1-1 octave bands and third octave bands. Octave bands contain a range of frequencies the upper limit of which is double the frequency of the lower limit (or $f_{upper} = 2\ f_{lower}$). The third octave band is defined by the limits $f_{upper} = 2^{1/3}\ f_{lower}$. All frequency bands are usually referred to as Centre Frequency which is the geometric mean frequency of the band; ($fcentre = \sqrt{f_{upper}}\sqrt{f_{lower}}$).

1.5.6 Background Noise

When sound measurement for instance on a machine is carried out, it is important that the background noise level is so low, that it does not have any influence on the result.

This can be tested in the following manner.

Measure the sound at the position where it should be measured with the source (machine) running. Switch off the machine and measure the sound level without the machine running.

- If the difference between these two readings is less than 3dB measurements should be stopped until the background noise has been reduced.
- If the difference is between 3 and 10 dB use the curve to correct the measured value as shown in fig.5.
- If the difference is more than 10 dB, the background noise may be ignored.

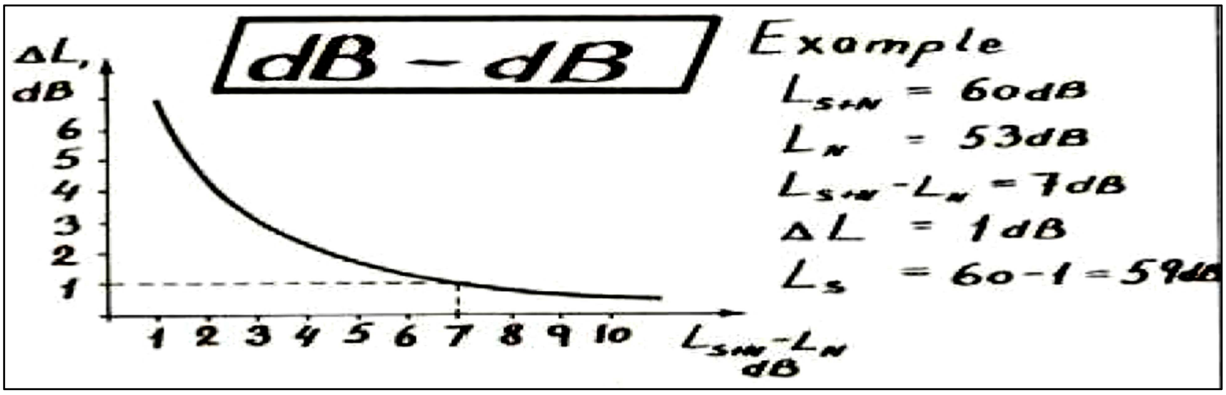

FIG.5 Curve for subtraction of background noise in dB [41]

1.5.7 Masking

The term ‘Masking’ is used about the phenomenon that the presence of a given sound can make another sound inaudible.

1.5.8 Equivalent Sound Level - Leq

Very often, noise levels fluctuate or vary randomly with time, as in case with factory and community noise. The correct representation of noise level in this kind of situation is given by the equivalent continuous level, Leq measured in dB (A).

The Leq level is a measure of the energy content of the noise over the measurement period.

Equivalent Sound Level - Leq - can be expressed as

$$Leq = 10 \log [(1/T) \int pA^2 \, dt/pref^2]$$

Where

Leq = equivalent sound level (dB)

T = time period (s)

pA = sound pressure (Pa, N/m^2)

pref = reference sound pressure (20×10^{-6} Pa, N/m^2)

1.5.9 Sound Exposure Level (SEL)

It is defined as the L_{eq} value referred for one second, is useful for comparing individual noise event of different duration.

1.5.10 Noise Dose

The noise dose is variant of L_{eq} measurement for which the measurement time is fixed at eight hours. The only difference between noise dose and 8 hr. L_{eq} is that noise dose is expressed as a percentage of the allowable daily exposure, 100% corresponds to a L_{eq} level of 90 dB (A) for 8 hours.

Noise level dB(A)	Maximum exposure time per 24 hour
85	8 hours
88	4 hours
91	2 hours
94	1 hour
97	30 minutes
100	15 minutes
103	7.5 minutes
106	3.7 minutes
109	112 seconds
112	56 seconds
115	28 seconds
118	14 seconds
121	7 seconds
124	3 seconds
127	1 second
130–140	less than 1 second
140	**NO EXPOSURE**

TABLE.3 Maximum Recommended Noise Dose

1.6 SOUND LEVEL METER

Many types of measuring systems can be used for the measurement of sound depending on the purpose of the study, the characteristics of sound and the extent of information that is desired about the sound. The various elements in a measuring system are:

a. the transducer; that is, the microphone;

b. the electronic amplifier and calibrated attenuator for gain control;

c. the frequency weighting or analyzing possibilities;

d. the data storage facilities;

e. the display.

Not all elements are used in every measuring system. The microphone can, for instance, be connected to a sound level meter or directly to a magnetic tape recorder for data storage and future measurement or reference. An example of the components of the sound level meter is shown in Figure 6.

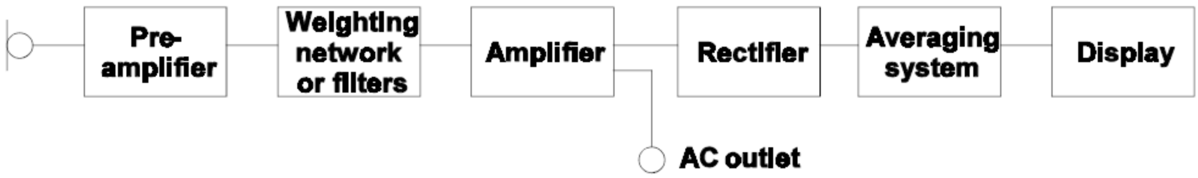

FIG.6 Sound level meter block diagram [46]

The two main characteristics are:

1. The frequency response: that is, the deviation between the measured value and the true value as a function of the frequency. As the ear is capable of hearing sounds between 20 Hz and *20* kHz, the frequency response of the sound level meter should be good, with variations smaller than 1 dB, over that range.

2. The dynamic range: that is, the range in dB over which the measured value is proportional to the true value, at a given frequency (usually 1000 Hz). This range is limited at low levels by the electrical background noise of the instrument and at high levels by the signal distortion caused by overloading the microphone or amplifiers.

Description

A sound level meter is an instrument designed to measure sound pressure levels. Today such instruments can be anything from simple devices with analogue filters and detectors and a moving coil meter to advanced digital analyzers. The microphone converts the sound pressure to an electrical signal, which is amplified and passes through various filters. After this the signal is squared and averaged with a detector, and the result is finally converted to decibels and shown on a display.

1.6.1 Elements of sound level meter

1. Microphone: Most measurement microphones generate a voltage that is proportional to the sound pressure at the microphone and is the electrical analog of sound waves impinging on the microphone's diaphragm. The particular mechanism that converts the pressure variation into sound waves signal. Different types of microphones are:

a. Capacitor (Condenser) Microphone

b. Pre-polarized Microphone

c. Piezoelectric Microphone

2. Amplifier: It amplifies the signal from microphone sufficiently to permit measurement of low SPL. It amplifies sound over a wide frequency range. It maintains the amplification constant.

3. Rectifier: It rectifies the signal from analog signal to digital signal.

4. Smoothing circuit: The circuit through which the sound waves pass.

5. Meter: It is the part of the sound level meter by which observation are taken.

FIG.7 Sound level meter

Chapter 2

TRAFFIC NOISE

2.1 INTRODUCTION

Urban traffic noise is one of the most pervasive types of noise pollution and generally considered more intrusive than other types of noise such as industrial noise, airport noise and community noise. The European Commission published the Green paper on future noise policy in 1996, where the statistical data showed that nearly 20% of people in the European Union were suffering from the impact of unacceptable urban noise level which mainly came from traffic. Road traffic generates noise pollution that can result in auditory and non-auditory health effects. Such noise can cause both short term as well as long term psychological and physiological disorders, particularly among those living, working or remaining in close proximity to roads. The major contribution of the traffic noise, towards overall noise pollution scenario, is a well-known established fact. It is estimated that 55% of the noise is due to transport sector and because of this there is a 2% reduction in GDP in UK alone. Coupled with 7% traffic growth per annum, the problem of vehicular noise poses a serious threat to the mankind.

Highway noise is the sum total of the noise produced at the observer point by all the moving vehicles on the highway. Thus the fundamental component is the noise produced by the individual vehicles, which depend on the vehicle type and its mode of operation. The overall noise is also dependent on the characteristics of the vehicle flow and the relative proportions of the vehicle types included in the flow. Knowledge of these factors is thus necessary to define the characteristics of highway noise and to subsequently predict the associated noise level in the surrounding area. The amount of information required depends on the degree of accuracy desired in the predictions, which in turn is a function of the method selected to characterize the temporal variation of the noise. Thus the complexity of highway noise model will depend on the noise descriptor selected. Traffic noise models vary in several respects but overall, their methodologies are similar with the A-weighted equivalent noise level Leq the most common descriptor used.

2.2 HIGHWAY NOISE DESCRIPTORS [28]

The following descriptors are in common use:

2.2.1 Percentile Exceeded Sound Level, L_X

This defines the sound level that has been exceeded **"**X**"** percent of time in a measurement period. The value of the sound level history over a given period of time is presented in the form of a cumulative distribution. The percentile exceeded sound levels most commonly used are L_{10} and L_{50}.

2.2.2 Equivalent Continuous (A-Weighted) Sound Level, L_{eq}

Equivalent continuous (A-weighted) sound level is defined as the steady sound level that contains the same amount of acoustic energy as the fluctuating level over the prescribed period of time. Common prescribed periods are one hour (L_{1h}), 24 hours (L_{24h}), and the day time hours (7 A.M. to 10 P.M.) (L_d), and the night time hour (10 P.M. to 7 A.M.) (L_n),

$$L_{eq} = 10 \log_{10} \frac{1}{T}\int_{O}^{T}\left[\frac{p}{p_{ref}}\right]^2$$

Where,

T = Total measurement time

P = A-weighted instantaneous acoustic pressure

P_{ref} = reference acoustic pressure = 20 μ Pa

2.2.3 Day Night Average Sound level, L_{dn}

This is an average sound level taken over a 24 hours period, 10 dB is added to account for the increased undesirable effect of noise at night. This is used to indicate the tolerance of people to noise at various times of the day.

2.2.4 Traffic Noise Index (TNI)

The traffic noise index is used to describe community noise. The TNI takes into account the amount of variability in observed sound levels, in an attempt to improve the correlation between traffic noise measurements and subjective response to noise.

The traffic noise index is defined by

$$TNI = 4(L_{10} - L_{90}) + L_{90} - 30 \text{ dB}$$

Where,

L_{10} = 10 percentile exceeded sound level

L_{90} = 90 percentile exceeded sound level

All these are in dB and measured during 24 hours period.

2.2.5 Noise Pollution Level (NPL)

Noise pollution level is sometimes used to describe community noise which employs the equivalent continuous (A-weighted) sound level and the magnitude of the time fluctuations in levels.

$$L_{NP} = L_{eq} + 2.5\sigma \text{dB}$$

Where,

σ = standard deviation of the instantaneous sound level

L_{eq} = equivalent continuous sound level

Out of the above, the two noise descriptors which have been mostly used in many countries to describe Highway Noise are L_{10} and L_{eq} levels.

2.3 VEHICLE NOISE

Before discussing the objective measurements of noise produced by road traffic itself, it is necessary to consider the noises emitted by individual vehicles.

2.3.1 Vehicle Noise Sources

The noise produced by a vehicle is dependent on the mode of operation of the vehicle. Noise can be considered to be produced by two major sources. They are:

(1) **Power plant and transmission noise source**

(2) **Running gear noise sources**

Power plant and transmission noise source include engine, exhaust, intake, cooling system and drive train noise. Running gear noise source includes the tire-road interaction, differential and propulsion shaft noise etc. Noise from the power plant increase as engine speed increases while noise from tire increases as vehicle speed increases.

Vehicles tend to operate at a nominally constant engine speed, so that engine and exhaust noise do not vary appreciably with vehicle speed.

Therefore, at lower highway speeds the engine-exhaust noise is dominant, while at higher vehicle speeds tire-pavement interaction becomes the dominant source of noise.

2.4 EFFECT OF VARIOUS FACTORS ON TRAFFIC NOISE

Rapidly changing population patterns on the national scene and developed public expectancy in terms of environmental effects have generated the requirement to furnish environmental impact statement. The result from the traffic noise is more complicated due to the facts that highways are not flat, straight or free from natural terrain variation. The factors like vehicle speed, density, traffic mix, width of median and number of lanes are not constant. Therefore, for traffic noise each of these parameters is taken into account.

Traffic noise depends on the following factors

2.4.1 Traffic Parameters

(i) Vehicle volume

(ii) Vehicle mix

(iii) Average speed

2.4.2 Roadways characteristics

(i) Pavement width

(ii) Flow characteristics

(iii) Gradient

(iv) Surface finish

2.4.2 Observer characteristics

(i) Observer distance

(ii) Element size

(iii) Shielding

(iv) Observer relative height

Traffic parameters

Traffic Volume, Q

The noise level near the highway depends on the number of vehicles. The noise level increases with an increase in traffic volume.

Traffic volume is defined as the total number of vehicles flowing per hour. The numbers of vehicles passing through a fixed point on the road are to be counted.

The traffic volume may be sub grouped into heavy vehicles and automobiles for duration of fifteen minutes. Several such samples are to be taken in different time slots ranging from 9.00 A.M. to 5.00 P.M.

Speed of Vehicle, V

If the vehicle is travelling within the limited range of road speeds, the noise produced is related to the engine, which would vary with each vehicle type. Many vehicles were either accelerating or decelerating when passing the measurement position. Thus the inclusion of the term for the speed of the vehicle, in urban area becomes meaningless.

Roadway Characteristics

The following road parameters have been found to influence the transmission of sound waves:

(i) Pavement width

(ii) Flow characteristics

(iii) Gradient

(iv) Surface finish

Observer Characteristics

Equivalent Distance from Roadways, D_E

Traffic noise diminishes from the source at the rate of 3 to 4.5 dB (A) per doubling of distance on ground cover. Noise levels are computed on the basis of a single equivalent lane located at

$$D_E = \sqrt{D_N \ D_F} \text{ in meters}$$

Where, D_N and D_F are observer distance to the Centre of the near and far lanes respectively.

2.5 METHOD OF PREDICTION

Several investigators have tried to estimate the traffic noise with the help of mathematical expression in terms of the various parameters. Basically two approaches have been used for predicting the traffic noise. Viz,

(1) Nomograph procedure
(2) Computerized prediction

Prediction of Highway Noise by Nomograph Procedure

Nomograph procedure is valid for moderately high volume of freely flowing traffic on infinitely long, unshielded, straight, level roadways. The step by step procedure involves a determination of L_{10} and L_{eq} for a straight roadway segments at a single observer position.

A curved road may be considered to be straight if it deviates from straight by less than 10 percent of the observer distance **"**D**"** for a distance **"**5D**"** from the nearest point. This tolerance is illustrated in Fig.8.

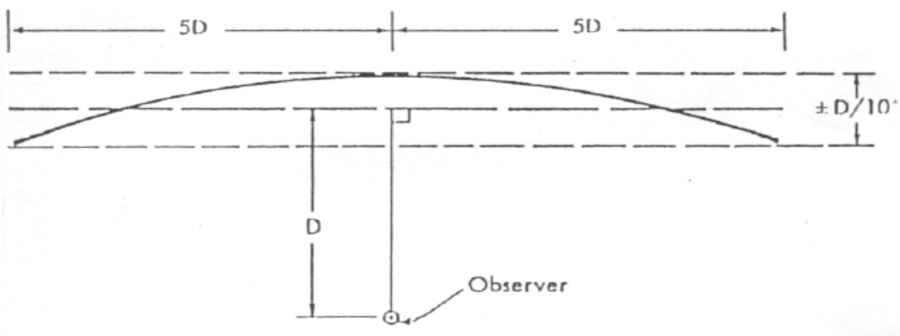

FIG.8 Permissible curvature for approximately straight roads [43]

For more than one roadway, the noise must be computed separately for each roadway, by considering perpendicular distance from the observer to each roadway.

A curved road may be divided into two or more approximately straight segments as shown in Fig.9.

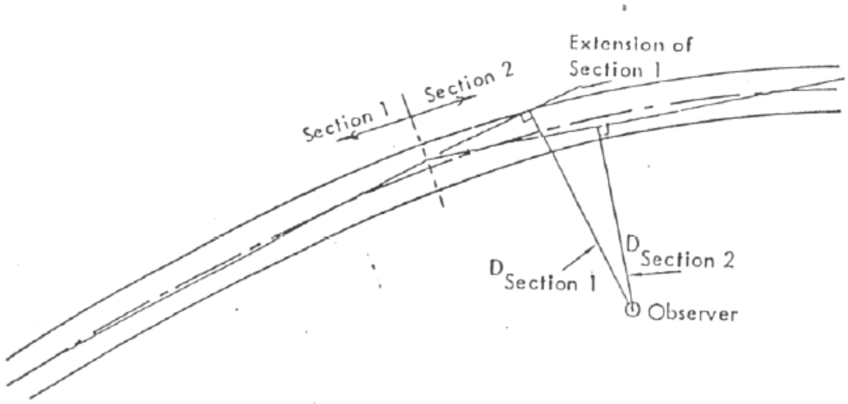

FIG.9 Curved Roadway approximated by two straight sections [43]

If the highway is divided into sections, or if there is more than one highway then the noise levels associated with each are combined, using the expression.

$$L_{10}\text{ total} = 10\log_{10}[10^{L_1/10} + 10^{L_2/10}]$$

Where,

$L_1 = L_{10}$ for section 1

$L_2 = L_{10}$ for section 2

Adjustment to the Nomograph Value

Road Segment

For practical purposes, a road segment can be considered an infinitely long highway if it extends in each direction a distance of at least $4D_N$. If the segment does not meet this criterion, an adjustment is made to decrease the L_{10} level because the segment is finite. The amount of this decrease is obtained from Fig.10. This figure is also valid for semi-infinite roadways.

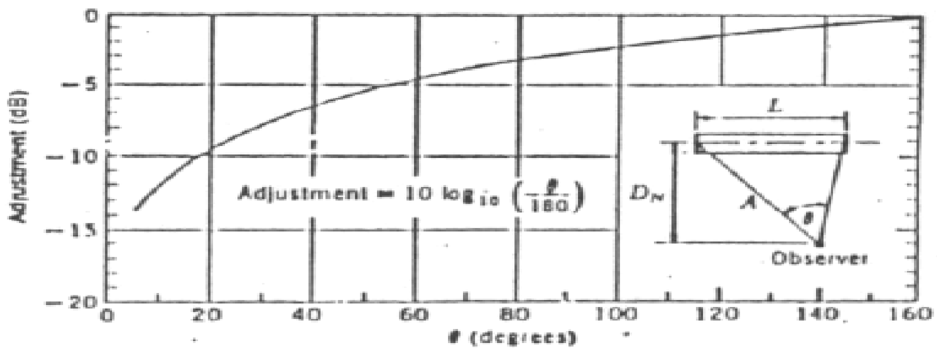

FIG.10 Adjustment of Nomograph values for finite length [43]

Road Surface

For vehicles travelling on very rough or very smooth pavement, the basic noise level computations are adjusted upward or downward, as the case may be, by 5 dB, in accordance with Table.4. For the great majority of new surfaces, no adjustment is needed. Occasionally an old surface, worn badly by studded tires, is encountered for which a 5 dB positive adjustment is justified. Less frequently, a very smooth coated surface warrants a 5 dB negative adjustment.

Type of surfaces	Description	Adjustment
Smooth	Very smooth, seal coated asphalt pavement	-5
Normal	Moderately rough asphalt concentrate surface	0
Rough	Asphalt pavement with large voids (13mm or larger in diameter) and grooved concrete	+5

TABLE.3 Adjustment to Automobile noise levels for various road surfaces

Road Gradient

The positive adjustments to account for the increased noise of trucks on gradients are shown in Table.5. These adjustments are made only to truck noise levels, and are never negative, that is there is no adjustment for a downhill gradient. In most situations where the two directional lanes appear together on a gradient, the adjustment may be applied equally to both sides of the highway without regard to whether the near lane is an up gradient or a down-gradient.

Gradient %	Adjustment
<2	0
3-4	+2
5-6	+3
>7	+5

TABLE.4 Adjustment to truck noise levels For various road gradients

As is seen from above discussions any mathematical model which is to be used for predicting L_{10} or L_{eq} level must include the following parameters:

1. Total vehicle volume/hr.
2. Percentage of heavy vehicles
3. The distance of the measurement point from the roadway
4. Average vehicle speed

Inclusion of vehicle speed as a parameter may be a difficult task and many models do not include this. The distance parameter can also be ignored if the measurement/reference point is not varied.

CHAPTER 3

ARTIFICIAL NEURAL NETWORK

3.1 INTRODUCTION

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

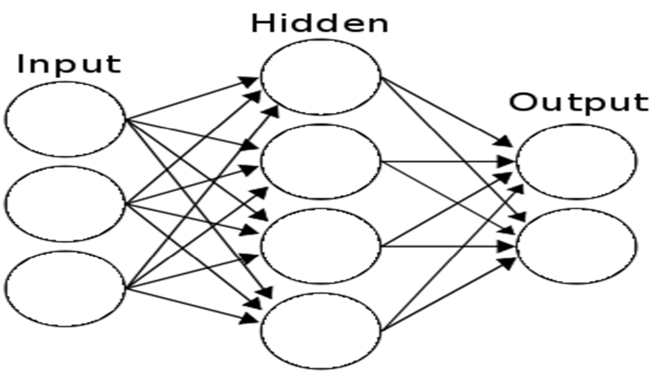

FIG.11 Neural Network [46]

An artificial neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain.

3.2 BACKGROUND [46]

The original inspiration for the term Artificial Neural Network came from examination of central nervous systems and their neurons, axons, dendrites, and synapses, which constitute the processing elements of biological neural networks investigated by neuroscience.

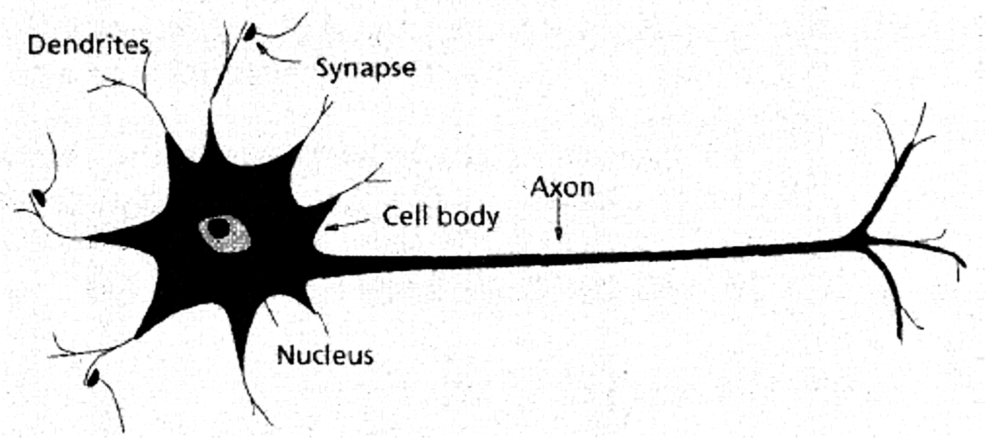

FIG.12 Biological Neuron [9]

In an artificial neural network, simple artificial nodes, variously called “neurons“, “neurodes”, “processing elements” (PEs) or “units”, are connected together to form a network of nodes mimicking the biological neural networks — hence the term “artificial neural network”. Generally, it involves a network of simple processing elements that exhibit complex global behavior determined by connections between processing elements and element parameters.

Its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned.

Currently, the term Artificial Neural Network (ANN) tends to refer mostly to neural network models employed in statistics, cognitive psychology and artificial intelligence. Neural network models designed with emulation of the central nervous system (CNS) in mind are a subject of theoretical neuroscience and computational neuroscience.

3.3 NETWORK FUNCTION [36]

The word network in the term 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system. An example system has three layers. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called **"**weights**"** that manipulate the data in the calculations.

An ANN is typically defined by three types of parameters:

1. The interconnection pattern between different layers of neurons
2. The learning process for updating the weights of the interconnections
3. The activation function that converts a neuron's weighted input to its output activation.

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 by some weights. Data flows along these connections and is scaled during transmission according to the values of weights as shown in Figure.13.

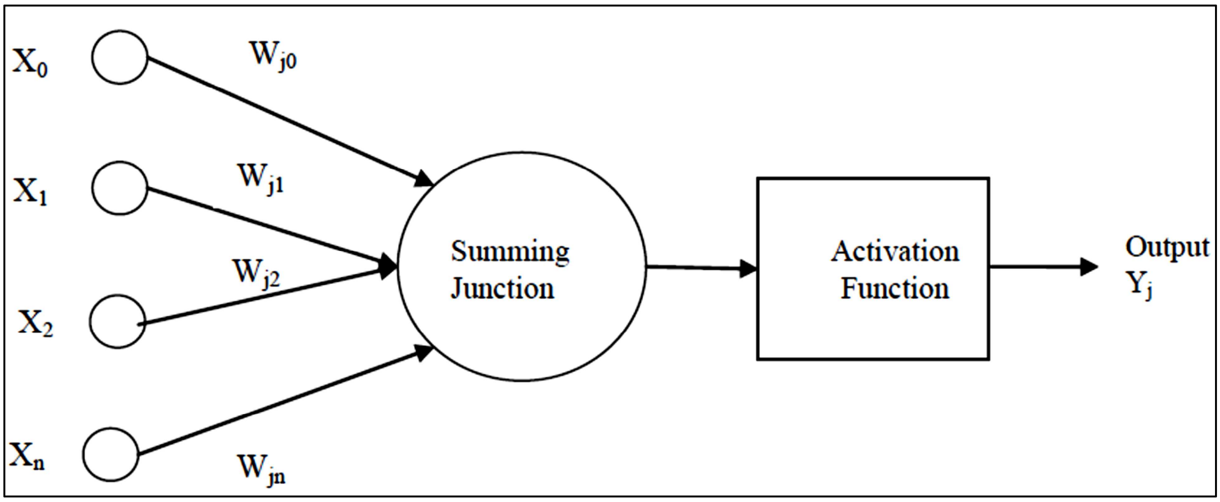

FIG.13 Nonlinear model of a neuron [36]

The relationship between the input signals X_0, X_1... X_n of neuron j and its output Yj is given by

$$\mathbf{I_j = \sum W_{ji} X_i \ \ (I \text{ varies from 0 to n})}$$

$$\mathbf{Y_j = f(I_j)}$$

where Wjo, Wj1,…, Wjn are the respective synaptic weights of neuron j, Ij is the linear combiner output due to input signals and f is the activation function. 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.

Weight & Bias

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 links, which are associated with weights. A bias acts exactly as a weight on a connection from a unit whose activation is always 1.

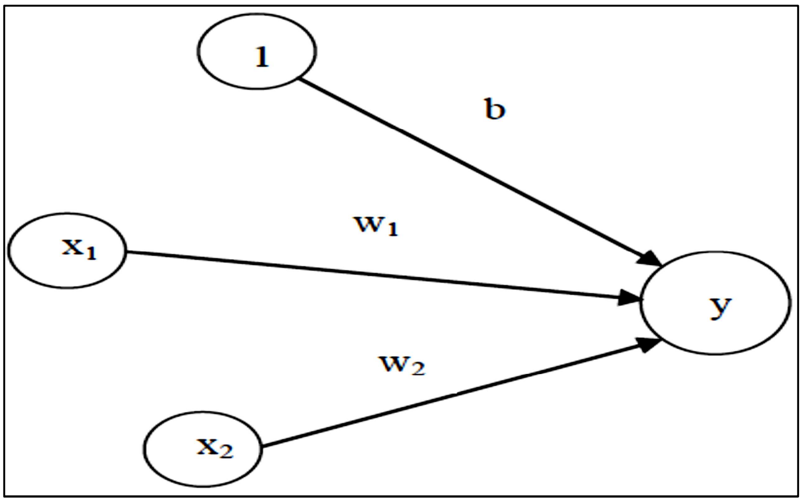

FIG.14 A simple net with bias [36]

Bias improves the performance of a neural network. If bias is present, then the net input is calculated as (Figure 14),

$$Net = b + \sum X_i W_i$$

where, Net = net input

b = bias

Xi = input from neuron i

Wi = weight connecting neuron i to output.

An activation function is used to calculate the output response of a neuron. The sum of a weighted input signal is applied to an activation function to obtain a response.

3.4 TRANSFER FUNCTION [46]

In ANN, each node has a set signal function that produces the output, which either goes to a number of other nodes or to the output of the entire network. The transfer function is the mechanism of translating input signal to output signal for each processing element. The three main type of transfer or activation function are:

1. Threshold Function
2. Linear function
3. Sigmoid function

First, there is the Threshold Function which takes on a value of 0 if the summed input is less than a certain threshold value (v), and the value 1 if the summed input is greater than or equal to the threshold value. Secondly, there is the Piecewise-Linear function. This function again can take on the values of 0 or 1, but can also take on values between that depending on the amplification factor in a certain region of linear operation. Thirdly, there is the sigmoid function. This function can range between 0 and 1, but it is also sometimes useful to use the -1 to 1 range.

3.5 LEARNING

Although a precise definition of learning is difficult to formulate, a learning process in the ANN context can be viewed as the problem of updating network architecture and connection weights so that a network can efficiently perform a specific task. The network usually must learn the connection weights from available training patterns. Performance is improved over time by iteratively updating the weights in the network. ANNs' ability to automatically 'learn from examples' makes them attractive and exciting.

Instead of following a set of rules specified by human experts, ANNs appear to learn underlying rules (like input-output relationships) from the given collection of representative examples.

3.6 LEARNING PARADIGMS [41]

There are three major learning paradigms, each corresponding to a particular abstract learning task. These are supervised learning, unsupervised learning and reinforcement learning.

3.6.1 Supervised learning

In this, every input pattern that is used to train the network is associated with an output pattern, which is the target or the desired pattern. A teacher is assumed to present during the learning process, when a comparison is made between the network's computed output and the correct expected output, to determine the error. The error can then be used to change the network parameters, which result in the improvement in performance.

3.6.2 Unsupervised learning

In this learning method, the target output is not presented to the network. It is as if there is no teacher to present the desired patterns and hence, the system learns of its own by discovering and adapting to structural features in input patterns.

3.6.3 Reinforcement learning

In this method, a teacher though available, does not present the expected answer but only indicates if the computed output in correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and penalty for the wrong answer. But, reinforcement learning is not one of the popular forms of learning.

3.7 LEARNING ALGORITHMS

Training a neural network model essentially means selecting one model from the set of allowed models that minimizes the error criterion. There are numerous algorithms available for training neural network models; most of them can be viewed as a straightforward application of optimization theory and statistical estimation. Most of the algorithms used in training artificial neural networks employ some form of gradient descent. This is done by simply taking the derivative of the error function with respect to the network parameters and then changing those parameters in a gradient-related direction. Evolutionary methods, simulated annealing, expectation maximization, non-parametric methods and particle swarm optimization are some commonly used methods for training neural networks.

The Back-Propagation Algorithm [40]

In order to train a neural network to perform some task, one must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (**EW**). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the **EW**.

The back-propagation algorithm is easiest to understand if all the units in the network are linear. The algorithm computes each **EW** by first computing the **EA** (error derivative with respect to activity level) the rate at which the error changes as the activity level of a unit is changed. For output units, the **EA** is simply the difference between the actual and the desired output. To compute the **EA** for a hidden unit in the layer just before the output layer, first identify all the weights between that hidden unit and the output units to which it is connected. Then multiply those weights by the **EA**s of those output units and add the products. This sum equals the **EA** for the chosen hidden unit. After calculating all the **EA**s in the hidden layer just before the output layer, we can compute in like fashion the **EA**s for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network.

This is what gives back propagation its name. Once the **EA** has been computed for a unit, it is straight forward to compute the **EW** for each incoming connection of the unit. The **EW** is the product of the EA and the activity through the incoming connection.

3.8 EMPLOYING ARTIFICIAL NEURAL NETWORKS

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data. However, using them is not so straightforward and a relatively good understanding of the underlying theory is essential.

- **Choice of model**: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.
- **Learning algorithm**: There are numerous trades-offs between learning algorithms. Almost any algorithm will work well with the correct hyper parameters for training on a particular fixed data set. However selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.
- **Robustness**: If the model, cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

With the correct implementation, ANNs can be used naturally in online learning and large data set applications. Their simple implementation and the existence of mostly local dependencies exhibited in the structure allows for fast, parallel implementations in hardware.

3.9 APPLICATIONS [46]

The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

Real-life applications

The tasks artificial neural networks are applied to tend to fall within the following broad categories:

- Function approximation, or regression analysis, including time series prediction, fitness approximation and modeling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Data processing, including filtering, clustering, blind source separation and compression.
- Robotics, including directing manipulators, Computer numerical control.

Application areas include system identification and control (vehicle control, process control), quantum chemistry, game-playing and decision making (backgammon, chess, poker), pattern recognition (radar systems, face identification, object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications (automated trading systems), data mining (or knowledge discovery in databases, "KDD"), visualization and e-mail spam filtering.

CHAPTER-4

LITERATURE REVIEW

INTRODUCTION

Traffic noise prediction models are required means in designing new highways and other roads or redesigning traffic flow in existing roads to have comfortable traffic noise conditions. In the last few years, a number of prediction tools have been created to estimate noise levels in several countries. For instance, Pamanikabuda.P [13] formulated a model of highway traffic noise based on vehicle types in Thailand. Banerjee, Chakraborty et al. [26] developed a model of road traffic noise in the industrial town of Asansol, India. A GIS based road traffic noise prediction model was developed for use in China by Li et al. [12]. Calixto et al. [14] from Brazil developed a statistical model to estimate road traffic noise in an urban setting. Steele Campbell [11] has reviewed commonly used models like CORTN, STAMINA, FHWA etc. & the desired data for traffic noise prediction. Pamanikabuda.P, Tansatchab.M, Brown.A.L[25] build a highway traffic noise simulation model for free-flow traffic conditions in Thailand employing a technique utilizing individual vehicular noise modeling and provides a more accurate measurement of noise energy from each type of vehicle under real running conditions. Banerjee, Chakraborty et al. [27] evaluates factors that significantly influence the equivalent road traffic noise level.
All the above mentioned and important works are as follows:

Johnson D.R. and Saunders E.G [1]

They described road side surveys of the noise emitted by freely flowing traffic on sites ranging from motorways to urban roads. Sites were generally unobstructed but a few tests were made in places with buildings adjacent to the roadway. The survey also included measurements on two sites involving road gradients. The results provide an indication of present day traffic noise conditions against which future comparisons may be made and also show how basic variables such as traffic density, speed and composition, and distance from roadside affect the observed patterns of noise. Agreement between the experimental data and theoretical analysis of simplified traffic flow forms the basis of a method for predicting the median Sound level produced under any given set of traffic conditions. The reliability of the method, provided that due allowance is made for possible ground attenuation effects, is demonstrated using the results of the survey.

Cannelli G.B. [2]

This work described that an objective survey was made of rush-hour traffic noise in Rome, on a statistically representative number of sites included in an area covering the historical Centre. The mean values of the statistical noise levels L_{90}, L_{50} and L_{10} i.e. of the noise levels exceeded for 90 percent, 50 percent and 10 per cent, respectively, of measuring time, were very close to those obtained during an investigation in Madrid and much higher than data from a 'London Noise Survey'. For the purposes of a subjective evaluation of noise in various types of site in Rome, the nuisance indices of noise proposed by a few investigators were also determined and compared against each other.

Gilbert D. [3]

This work developed an equation for predicting L10 noise levels for roads where interrupted flow traffic exits. This summarizes the initial work carried out at Imperial College to develop provisional prediction equation. It then describes how the equation was tested and modified by using data recently acquired at Sheffield and Rotherham. The provisional equation includes a variable, the index of dispersion, whose value cannot at present be predicted. But an alternative equation is described which uses only currently predictable variables. It is based on the data from Sheffield and Rotherham.

Ko N.W.M. [4]

This work presents the findings of a further analysis of the results of road traffic noise measurements made in a high-rise city. The means and standard deviations of the sound pressure levels within the industrial, commercial, commercial/residential and residential areas are only very marginally different from one another.

Bjorkman M. [5]

This paper reviewed certain field investigations which have shown that the correlation between the extent of annoyance due to road traffic noise and the noise dose expressed in Leq is rather poor. A higher correlation was found when the expression of the noise dose was based upon the maximum noise level (MNL) from the single noisiest event. To determine the relation between Leq and MNL according to different principles, 24-h measurements were made for a period of 5 days in 18 streets with various types of traffic noise exposure. Analyses were made of the variation in MNL during different times of day and of the correlation between MNL during different times of day and of the correlation between MNL and other noise indices. Leq, and MNL during day, evening and night were not related. It is suggested that investigations be performed focusing on the extent of annoyance in streets with similar Leq values where the MNL for day, evening and night is different.

Kumar Krishan and Jain V.K [6]

They carried out a survey of traffic noise in the city of Delhi in order to examine the nature and levels of noise inside various types of vehicle. The study involved measurements of average A-weighted levels and power spectra of noise inside buses, auto-rickshaws, cars and trucks from which L10, L50, L90 and Leq levels were estimated. It is found that noise levels in auto-rickshaws are the highest, followed by trucks, buses and cars. The power spectra fall four types of vehicle exhibit rather similar behavior.

Cammarata G, Cavalier S, Fichera A [7]

This paper reviewed the application of neural networks (NNs) to the problem of prediction of noise caused by urban traffic. The most representative physical variable quantifying noise emissions is the equivalent sound pressure level up to now it was identified on the basis of semi-empirical models, typically regression analysis, which generally do not provide very accurate approximations of the trend followed by sound pressure level The authors had attempted to overcome this difficulty by adopting a neural approach based on a Back-Propagation Network (BPN). Results obtained by the comparison of the BPN approach with those provided by selected relationships found in relevant literature, show how good is the approach proposed. The neural solution to the problem was shown the necessity, in certain phases, of a set of acoustic measurements which is as free as possible of error. The complexity of error identification by means of classical approaches has led the authors to explore the possibility of a neural solution to this problem as well. The authors therefore proposed the use of a neural architecture made up of two cascading levels. At the first level a supervised classifying network, the 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.

Dougherty Mark [8]

Attempted to summarize the findings of a large number of research papers concerning the application of neural networks to transportation. A brief introduction to neural networks is included. The paper surveys both the application areas found to be fruitful and the range of neural network paradigms which have been used. A particular weakness noted in much of the work is the informal approach taken to detailed analysis of the results of the research. It was postulated that a more rigorous approach to matters such as comparison with other techniques and also the methodology used to design the neural networks would help a clearer picture to emerge as to best practice and future research directions.

Jain Ani1 [9]

Discussed the motivations behind the development of ANNs , describe the basic biological neuron and the artificial computational model, outline network architectures and learning processes, and present some of the most commonly used ANN models. Finally conclude with character recognition, a successful ANN application.

Wilkinson P and Reuben R L [10]

The application of an artificial neural network to classification tool wears states in face milling. The input features were derived from measurements of acoustic emission during machining and topography of the machined surfaces. Five input features were applied to the back-propagating neural network to predict a wear state of light, medium or heavy wear. They present results from milling experiments with multi- and single-point cutting and compare the neural network predictions with observed cutting insert wear states.

Campbell Steele [11]

Traffic noise prediction models in the 1950s and 1960s were designed to predict a single Vehicle sound pressure level Lp at the roadside. These models were based on constant speed experiments, the predicted levels then being expressed as functions of speed, and with zero acceleration. Later models were not intended to predict single vehicle levels but to predict the equivalent continuous level Leq for traffic over a chosen period. Still later models predicted Leq under interrupted and varying flow conditions. Early models predicted linear levels whereas the later models predicted A-weighted levels. Several more recent models predict one-third octave band spectra. Early models assumed single point sources, some assumed short line sources, later ones double point, and even one with thirty-two point sources; some with different spectra. Six commonly used models and others under development are reviewed.

Bengang Lia, Shu Taoa, Dawsona R W, Jun Caoa, Kinche Lamb [12]

They predicted a suitable road traffic noise model for use in China. This model is based on local environmental standards, vehicle types and traffic conditions. The model was accurate to 0.8 dBA at locations near the road carriage way and 2.1 dBA within the housing estate, which is comparable to the FHWA model. An integrated noise-GIS system was developed to provide general functions for noise modeling and an additional tool for noise design, where a new interaction mode in ‘‘WHAT IF Question/Explanation’’ format was used. Application of this system offered improvements in the efficiency and accuracy of traffic noise assessment and noise design.

Pamanikabud Pichai, Vivitjinda Prakob [13]

They formulated a model of highway traffic noise based on vehicle types. They collected data from local highways in Thailand with free-flow traffic conditions. First, data on vehicle noise was collected from individual vehicles using sound level meters placed at a reference distance. Simultaneously, measurements were made of vehicles spot speeds. Secondly, are data for building the highway traffic noise model. This consists of traffic noise levels, traffic volumes by vehicle classification, average spot speeds by vehicle type, and the geometric dimension of highway sections. The free-flow traffic noise model was generated from this database. A reference energy mean emission level (the basic noise) level for each type of vehicles was developed based on direct measurement of Leq (10 s) from the real running condition of each type of vehicles. Modification of terms and parameters are used to make the model fit highway traffic characteristics and different types of vehicle.

Calixto Alfredo, B Diniz Fabiano, H T Zannin Paulo [14]

The paper refers to a study of the problem of traffic noise on roads which have been transformed into big avenues in the city of Curitiba. Noise levels are measured and the impacts suffered by the community documented. Around the main roads inside the urban perimeter of Curitiba, simultaneous measurements were done regarding noise levels, vehicle flow and traffic composition and thus some mathematical models have been developed in order to estimate those sound pressure levels. The measured levels compared with the calculated ones obtained from the mathematical model and the German Standard RLS-90 as well. The validity of the mathematical models was confirmed, as well as the applicability of the calculation method adopted by the German Standard RLS-90. Finally, the mean traffic noise levels around those roads and the noise limits of the municipal law 8583/1995 were examined and it was confirmed that people living or working in these areas are exposed to noise levels beyond the legislated norms.

Nagesh D S, Datta G L [15]

Bead geometry (bead height and width) and penetration (depth and area) are important physical characteristics of a weldment. Several welding parameters seem to affect the bead geometry and penetration. It was observed that high arc-travel rate or low arc-power normally produced poor fusion. Higher electrode feed rate produced higher bead width making the bead flatter. Current, voltage and arc-travel rate influence the depth of penetration. The other factors that influence the penetration are heat conductivity, arc-length and arc-force. Longer arc-length produces shallower penetration. Too small arc-length may also give rise to poor penetration, if the arc-power is very low. Use of artificial neural networks to model the shielded metal-arc welding process is explored in this paper. Back-propagation neural networks are used to associate the welding process variables with the features of the bead geometry and penetration. These networks have achieved good agreement with the training data and have yielded satisfactory generalisation. A neural network could be effectively implemented for estimating the weld bead and penetration geometric parameters. The results of these experiments show a small error percentage difference between the estimated and experimental values.

Gaja E, Gimenez A, Sanchoa S, Reig A [16]

This paper summarizes 5 years of continuous noise measurements carried out at one of the most important squares in Valencia (Spain). The chosen square is a clear hotspot for traffic noise in a large city. The aim of this study is to determine the appropriate measuring time in order to obtain a 24-h noise level suitable to represent the annual equivalent level. Findings allow reaching a number of conclusions in terms of the most suitable urban traffic noise measurement techniques. A random day strategy for sampling is found to give a more accurate representation than a consecutive day’s strategy. If the sampling strategy involves measurements on randomly-chosen days, then at least 6 days should be used.

Klaeboe R, Amundsen AN H, Fyhri A, Solberg S [17]

Estimated exposure–effect relationships between the levels of road traffic noise at the most exposed side of a dwelling’s facade and the residents’ reactions to road traffic noise. The relationships are based on five Norwegian socio-acoustic studies featuring 18 study areas from two cities and a total of near 4000 respondents. The survey questionnaires distinguish between noise annoyance experienced right outside the apartment and when indoors. Exposure–effect relationships for all degrees of annoyance are estimated simultaneously from ordinal logit models. These predict road traffic noise annoyance when right outside the apartment and when indoors, respectively, as a function of the road traffic noise level outside the most exposed facade. Separate analyses indicate that Norwegians react stronger to road traffic noise than results from a recent compilation of socio-acoustic surveys would lead one to believe. People having inferior single glazing windows were reported higher indoor annoyance.

Sopasakis Alexandros [18]

Reviewed a stochastic process generated from an ergodicity satisfying Markov chain whose system dynamics sample from the Gibbs distribution. Specially, employed Arrhenius microscopic dynamics in order to also capture non-equilibrium behavior and monitor the states favored by the system through its time evolution. Monte Carlo simulations of this traffic system provide information and statistics regarding free-flow, “synchronized” traffic, jam wave formation or dissipation, “stop and go” regimes and a variety of interesting such traffic behavior, summarized in, among others, the fundamental diagram. Generalizations to the current model and a number of ideas for further studies are proposed.

Manoel Joel, Lenzi Arcanjo, Zannin Paulo [19]

This work analyses the effects of traffic composition on the noise generated by typical Brazilian roads. Traffic composition is defined as the percentage of heavy vehicles with respect to the total number of vehicles. Measurements were made from Monday to Friday, 6:00 to 10:10 a.m. A total of 149 measurements were made on three roads. For each the percentile level L10 and the equivalent level Leq were measured. These levels were plotted against the composition of the traffic and empirical expressions were obtained with reasonably good correlation indexes. The results are compared to those of Crompton and Gilbert found for UK roads.

Tyagi Vikrant, Kumar Krishan, J Vinod [20]

Traffic noise attenuation at different 1/3-octave frequencies is measured at three vegetation sites and a control site in Delhi, the capital city of India. The study indicates that attenuation generally increases with frequency. At low frequencies, maxima (between 10 and 16 dB) in relative attenuation are observed in the frequency interval between 315 and 400 Hz. Comparatively greater relative attenuation (>20 dB) is observed in the high frequency range between 10 and 12.5 kHz. A significantly higher relative attenuation of more than 24 dB is observed characteristically at 3.15 kHz at all the vegetation sites. The results indicate that vegetation belts could be used as effective barriers for traffic noise control along the roadsides.

Aleksendric D, Duboka C [21]

In this study, an artificial neural network technique was used to predict the cold performance of the automotive friction material. Cold performance was predicted for two cases: (i) before and (ii) after fading and recovery tests. Predictions were related to the brake factor *C* values versus 26 input parameters. The input parameters are defined by the friction material formulation (18 parameters), manufacturing conditions (5 parameters), and testing conditions (3 parameters). For these predictions, the five types of the friction materials were produced and tested. The quality of prediction was evaluated by comparison of the real results obtained during testing on the single-end full-scale inertia dynamometer and predicted ones.

The 15 different architectures of the artificial neural networks were investigated. The five training algorithms were employed for the artificial neural networks training.

Dae Seung Cho, Sungho Mun [22]

A highway traffic noise prediction model has been developed for environmental assessment in South Korea. The model is based on an outdoor sound propagation method and is fully compliant with ISO 9613 and the sound power level (PWL) estimation for a road segment, as suggested in the ASJ Model-1998 that is based on PWLs. Due to that model’s selection of two pavement types, such as asphalt or concrete pavement, an unacceptable traffic noise prediction is made in cases where the road surface is different from that on which the model is based. In order to address this problem, several road surface types are categorized, and the PWL of each surface type is determined and modeled by measuring the noise levels obtained from newly developed methods. An evaluation of the traffic noise prediction model using field measurements finds good agreement between predicted and measured noise levels.

Aluclu I, Dalgic A, Toprak Z F [23]

This paper describes noise–human response and a fuzzy logic model developed by comprehensive field studies on noise measurements (including atmospheric parameters) and control measures. The model has two subsystems constructed on noise reduction quantity in dB. The first subsystem of the fuzzy model depending on 549 linguistic rules comprises acoustical features of all materials used in any workplace. Totally 984 patterns were used, 503 patterns for model development and the rest 481 patterns for testing the model. The second subsystem deals with atmospheric parameter interactions with noise and has 52 linguistic rules. Similarly, 94 field patterns were obtained; 68 patterns were used for training stage of the model and the rest 26 patterns for testing the model. These rules were determined by taking into consideration formal standards, experiences of specialists and the measurements patterns. The results of the model were compared with various statistics (correlation coefficients, max–min, standard deviation, average and coefficient of skewness) and error modes (root mean square error and relative error). The correlation coefficients were significantly high, error modes were quite low and the other statistics were very close to the data. This statement indicates the validity of the model. Therefore, the model can be used for noise control in any workplace and helpful to the designer in planning stage of a workplace.

Dae Seung Cho, Sungho Mun [24]

The effects of vehicles and pavement surface types on noise were investigated at the Korea Highway Corporation’s Test Road along the southbound side of the Jungbu Inland Expressway, South Korea. The study was conducted in 2005 and 2006 through field measurements at nine surface sections of asphalt concrete and Portland cement concrete pavements using eleven vehicles. For the road noise analysis, the sound power levels (PWLs) of combined noise (e.g., tire/pavement interaction noise and power-train noise together) and tire/pavement interaction noise using various vehicles were calculated based on the novel close proximity (NCPX) and pass-by methods. Then, the characteristics of the PWLs were evaluated according to surface type, vehicle type, and vehicle speed. The results show that the PWLs of vehicles are diversely affected by vehicle speed and the condition of the road surface.

Pamanikabuda P, Tansatchab M, Brown A L [25]

The objective was to build a highway traffic noise simulation model for free-flow traffic conditions in Thailand employing a technique utilizing individual vehicular noise modelling based on the equivalent sound level over 20 s (Leq20 s). This Leq20 s technique provides a more accurate measurement of noise energy from each type of vehicle under real running conditions. The coefficient of propagation and ground effect for this model was then estimated using a trial-and-error method, and applied to the highway traffic noise simulation model. This newly developed highway traffic noise model was tested for its goodness-of-fit to field observations. The test shows that this new model provides good predictions for highway noise conditions in Thailand. The concepts and techniques that are modeled and tested in this study can also be applied for prediction of traffic noise for local conditions in other countries.

Banerjee D, Chakraborty S K, Bhattacharyya S, Gangopadhyay A [26]

This study evaluates factors that significantly influence the equivalent road traffic noise level, Leq and develops models for the industrial town of Asansol, India. The study shows that Leq values are mainly influenced by the hourly traffic volume. Day time data reveals a stronger relationship than night data. Principal component analysis was also used to identify dominating variables affects Leq.

Banerjee D, Chakraborty S K, Bhattacharyya S, Gangopadhyay A [27]

The objectives of the study were to monitor and assess the road traffic noise in its spatial temporal aspect in an urban area. The paper discusses the observations, results and their interpretation based on the study. Noise recordings from site, collected from April 2006 to March 2006, were used for statistical analysis and generation of various noise indices. Noise maps were also created for impact analysis and formulation of Noise Risk Zones. Mean Ldn value ranged between 55.1 and 87.3 dB (A). Day time Leq level ranged between 51.2 and 89.0 dB (A), where it ranged between 43.5 and 81.9 dB (A) during night. The study reveals that present noise level in all the locations exceeds the limit prescribed by CPCB. Based on the finding it can be said that the population in this industrial town are exposed to significantly high noise level, which is caused mostly due to road traffic.

Adeli Hojjat, Panakkat Ashif [29]

A probabilistic neural network (PNN) was presented for predicting the magnitude of the largest earthquake in a pre-defined future time period in a seismic region using eight mathematically computed parameters known as seismicity indicators. The indicators considered are the time elapsed during a particular number (n) of significant seismic events before the month in question, the slope of the Gutenberg -Richter inverse power law curve for the n events, the mean square deviation about the regression line based on the Gutenberg-Richter inverse power law for the n events, the average magnitude of the last n events, the difference between the observed maximum magnitude among the last n events and that expected through the Gutenberg-Richter relationship known as the magnitude deficit, the rate of square root of seismic energy released during the n events, the mean time or period between characteristic events, and the coefficient of variation of the mean time. Prediction accuracies of the model are evaluated using three different statistical measures: the probability of detection, the false alarm ratio, and the true skill score or R score. The PNN model was trained and tested using data for the Southern California region. The model yields good prediction accuracies for earthquakes of magnitude between 4.5 and 6.0. The PNN model presented in this paper complements the recurrent neural network model developed by the authors previously, where good results were reported for predicting earthquakes with magnitude greater than 6.0.

Can A, Leclercq L, Lelong J, Botteldooren D [30]

This paper compares two traffic representations for the assessment of urban noise frequency spectrum:(i) a static one, based on mean vehicle speeds and flow rates, (ii) a dynamic one, which considers vehicle interactions along the network. The two representations are compared on their suitability to match real on-field noise levels, recorded on a three lane quite busy street. Representation (i) fails in reproducing spectra envelopes that correspond to this site. In particular, it underestimates low frequencies, what can conceal the real impact of traffic flow on urban sound quality. Representation (ii) greatly improves estimation. It guarantees accurate environmental noise assessment, since it reproduces all traffic situations that are encountered in the site. Moreover, its 1s-based structure allows for the evaluation of spectra variations, with a good accuracy.

Givargis S, Karimi H [31]

This work presents an artificial neural network model to predict hourly A-weighted equivalent sound pressure levels (LAeq, 1h) for roads in Tehran at distances less than 4 m from the nearside carriageway edge. Their model uses the UK Calculation of Road Traffic Noise (CORTN) approach. Data were obtained from 50 sampling locations near five roads in Tehran at nearside carriageway edge distances of less than 4 m. The data were randomly assigned to training, testing, and holdout subsets. Model training was carried out using the training and testing subsets and comprised 60% and 20% of the data, respectively. Model validation was performed using the remaining 20% of data as a holdout subset. They examine the overall model efficiency using non-parametric tests, such as the Wilcoxon matched-pairs signed-rank test for the training step and the KolmogoroveSmirnov test for two independent samples for the validation step. Their results indicate that a neural network approach can be applied for traffic noise prediction in Tehran in a statistically sound manner. The Wilcoxon matched-pairs signed-ranks test detects no significant difference between the absolute testing set errors of the developed neural network and a calibrated version of the CORTN model.

Guarnaccia Claudia [32]

In this paper, the author presents the analysis of an intersection case study in proximity of Salerno University, performed by means of experimental measurements and software simulations. The chosen area presents interesting features because of the priority rights on the principal road and because of the relevant amount of vehicles and buses, mainly due to the University students and personnel that transit in the intersection, especially during rush hours. The aid of predictive software is highlighted, together with the shortcomings of a simulation strategy that does not take into account traffic dynamics. The analogy between electrical current and vehicular flow is sketched and used in the roads vehicles volume definition.

Wang Bo, Kang Jian [33]

In this research, two representative cities with different urban densities, Greater Manchester in the UK and Wuhan in China, were selected, which have low and high average urban density respectively, and also have considerable differences in building form and traffic pattern. In the meantime, these two cities have similar urban scale and traffic amount. In each city, based on the urban morphological analyses considering urban land-use, building and road density, and noise source distribution, a number of typical urban areas, 500 _ 500 m^2 each, were sampled. A noise-mapping software package was then used to generate generic noise maps, based on existing digital vector maps for terrain and building, and traffic data obtained by on-site measurements. The comparison results show that the average and minimum noise level in Greater Manchester samples is generally higher than that in Wuhan samples, while the maximum noise level in Wuhan samples is mostly higher. By developing a Matlab program, correlations have been analyzed between noise distributions and the urban characteristics relating to urban density, such as the road and building coverage ratio. Overall, comparisons between these two typical cities have shown significant effects of urban morphology on the traffic noise distribution.

Rahmani S, Mousavi S M., Kamali M J [34]

Two models for predicting in-city road-traffic noise pollution of Mashhad have been obtained. Traffic volume, composition, and speed have been chosen as model's parameters. Vehicles were classified into light cars and medium and heavy trucks. Reference emission level of each group was determined experimentally based on perpendicular propagation from central lane of traffic road. Simultaneous measurements of noise level and vehicle flow and composition were done. Two mathematical models have been proposed by the use of genetic algorithms which can be used for calculating Leq. These models have been validated against noise data. Subsequently, measured traffic noise has been compared with calculated Ones, using developed models, and a relatively good agreement has been obtained among them. The models are found accurate within ±1% and can be used for flat road noise prediction.

Molares Alfonso Rodríguez, Seoane Manuel A Sobreira, Herrero Julio Martín [35]

The inverse relation of the uncertainty of the equivalent sound pressure level to the square root of the number of vehicle pass-bys is investigated. The influence of the traffic spatial distribution is evaluated by means of a computer model, based on Monte Carlo and the Weyl–Ingard Theory. The model results are discussed and compared with experimental data. By least mean squares fitting of simulated results, a new expression is obtained for the sound pressure level uncertainty that takes into account the receiver position, road configuration and traffic flow balance. This expression explains the different values found in the literature and yields uncertainty values that may not be covered by the ISO 1996-2:2007 recommendation, in some specific circumstances. Finally the path for building traffic noise uncertainty maps is sketched out.

Kumar Kranti, Parida Manoranjan, Katiyar Vinod [36]

This paper aims to summarize the findings of research concerning the application of neural networks in traffic noise prediction. Modeling and prediction of traffic noise by means of classical approaches is a very complex and nonlinear process, due to involvement of several factors on which noise level depends. To overcome these problems, researchers and acoustical engineers have applied the artificial neural network in the field of traffic noise prediction. After a critical review of various neural network based models developed for road traffic noise prediction cited in the literature it was concluded that ANN based models were capable of predicting traffic noise more accurately and effectively as compared to deterministic and statistical models.

CHAPTER-5

EXPERIMENTAL INVESTIGATION & MEASUREMENTS

5.1 Noise problem overview

Traffic noise models are important in the design of both highway and non-highway road projects. Such models are also helpful tools when assessing current or envisioned changes to traffic noise conditions. Consequently, noise models are used extensively in the monitoring of environmental noise impact and the management of practical solutions to existing noise problems. All these models required to predict the sound pressure level specifically in terms of Leq and L_{10} (10 Percentile Exceeded Sound Level) based on the field measurement of different highway noise descriptors and traffic noise parameters. An investigation of the area revealed that the major source of noise pollution is the traffic noise with subsequently high percentage of heavy vehicles. The noise nuisance was heightened by the uncritical horn blustering, rapid acceleration and overtaking with an average vehicle speed of 40-55 km/hr.

5.2 Selection of site

For this study, a site was required on a national highway NH-64 passes through military area; the Patiala-Sangrur Highway was selected for experimentation. A site was chosen, at a distance of 1.5 km from Rajindra hospital, Patiala. This is the two lane straight patch with continuous flow of vehicles, a reasonably flat open area, free from large reflecting surfaces, such as parked vehicles, signs, buildings and any obstructions like traffic signal lights etc.

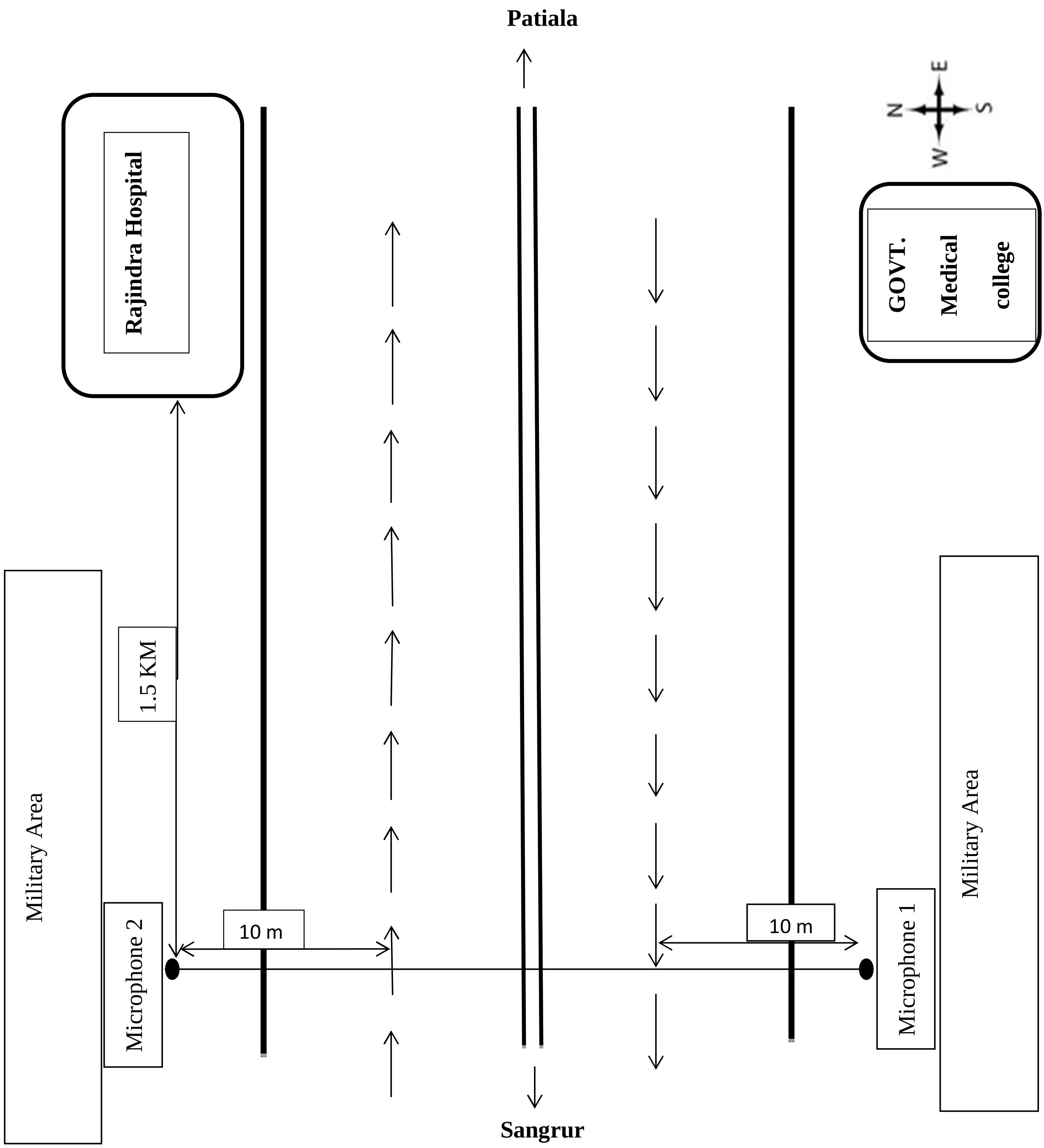

FIG.15 Site: Patiala-Sangrur Highway (NH-64)

5.3 Definition of problem

Today, because of the rapid development in the transportation sector, the number of vehicles on the Indian roads is increasing at a very fast rate. This leads to overcrowded roads and noise pollution that generate environment problem which inflicts serious damage to the health of human beings and lowers their labor productivity. Therefore, the control of traffic noise has become a matter of major concern for communities trying to maintain a satisfactory environment in which to live and work. So for the control of the traffic noise, first it should be fully understood. It is basically generated because of two major sources

- **Power plant and transmission noise source (**includes engine, exhaust, intake, cooling system and drive train noise.)
- **Running gear noise sources (**includes the tire-road interaction, differential and propulsion shaft noise etc.)

Several factors like type of roads, vehicle type, traffic mix, driving behavior, traffic flow, percentage of heavy vehicle, average speed, Pavement width, Surface finish, Observer distance, Shielding and many more which contribute their effect to the traffic noise.

No comparable advances have been made in many countries based on different highway noise descriptors and traffic noise parameters, but the highway noise descriptors, L_{eq} (in North America, Continental Europe) and L_{10} (in United Kingdom) are increasingly being used for quantitative assessment of nuisance associated with traffic noise. Further these models are unreliable for predicting highway noise in India because of different traffic condition and traffic characteristics.

This study is thus aimed to develop a more relevant and accurate free-flow traffic noise prediction model for highway in India, taking Patiala (Punjab) city as a representative city, based on L_{eq} and L_{10} as noise descriptors and traffic flow, percentage of heavy vehicle, average speed as traffic noise parameters. A large number of sets of data were recorded for 1 hr. duration on different dates and timings in a random or staggered manner in order to account for statistical temporal variations in traffic flow characteristics. To fulfill the above objective, Artificial Neural Network (ANN) approach has been applied for traffic noise modeling in the present study. The measured parameters were divided into two classes i.e. output parameters (L_{10}, L_{eq}) and input parameters (vehicle volume/hr., percentage of heavy vehicles and average vehicle speed) and further the input parameters are randomly subdivided into three set i.e. training, testing and validation. The ANN was first trained to map the input -output relationship and generalized the network using validation set. The prediction capability of ANN was checked for the given testing set of input parameters. A comparison is also made between experimental and ANN output parameters.

5.4 Measurement procedure

For traffic noise measurements at a suitable site systematic noise monitoring was done during April 2012 - May 2012 using Sound Level Meter (Cesva SC-310).

The sound level meter has been suitably calibrated. The microphone mounted on a tripod has been suitably level with air bubble.

The SLM was mounted at a height of 1.2 meter above the ground level and was located a distance of 10 m from the center of the road lane. Continuous data was recorded with Sound Level Meter during daytime from 9.00 A.M to 5.00 P.M at the selected site. The noise descriptors L_{eq}, L_{max}, L_{min} and L_{10} were measured for 15 min. duration in dB (A) weighting with slow response. Besides noise monitoring vehicles counts and vehicle speed, temperature were also measured continuously.

Lmax was the maximum noise level during the measurement period i.e. within 15 minutes.

Unusually high values of Lmax represent the cases of vehicles honking continuously or the vehicles are without proper silencers, etc.

Values of Lmin represent the minimum noise levels during the measurement period.

FIG.16 Sound level meter on a tripod with windscreen

FIG.17 Experimental site

5.5 Measurements

Data was measured at the selected site as per the described procedure.

Measured Parameters are:

Traffic volume

Traffic volume (number of vehicles passed during the measurement interval) was measured during the measurement period. Vehicles are categorized into 7 different types (Appendix-A) taking into account the Indian conditions.

Measurements for the 15 min. interval were repeated on different dates and timings in order to account for statistical temporal variations in traffic flow characteristics and hourly data for Leq and L_{10} has been calculated by taking the average of 4 readings of 15 minutes period and for traffic flow by addition of these 4 readings.

Average speed of vehicles

Average speed of vehicles was also measured with manual method by measuring the time taken by the vehicle to travel 100m distance.

Noise descriptors (L_{eq}, L_{max}, L_{min} and L_{10})

The noise descriptors L_{eq}, L_{max}, L_{min} and L_{10} were displayed on the SLM screen and were recorded in SLM memory.

Site: Patiala Sangrur Highway (NH-64) (1.5 km from Rajindra Hospital)

Measurement period: 15 minutes

Microphone at 10 meter from the center of the lane and at height of 1.2 meter

(MEASURED DATA FOR ALL DAYS)

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:21/03/12(Wednesday)							
09:00-10:00AM	1228	39.73	49.0	78.0	80.2	93.6	56.0
10:00-11:00AM	1267	32.20	47.3	77.5	79.3	91.8	55.9
11:00-12:00AM	1230	34.15	53.0	78.5	80.4	96.8	57.0
12:00-01:00AM	1310	32.06	48.0	77.8	79.9	91.3	55.6
Date:24/03/12(Saturday)							
09:00-10:00AM	1280	33.59	46.0	76.2	80.8	97.0	56.5
10:00-11:00AM	1295	35.52	45.9	76.8	79.6	92.8	57.3
11:00-12:00AM	1335	38.20	48.8	76.5	79.8	94.7	56.9
12:00-01:00AM	1250	31.60	49.4	77.2	80.7	96.0	57.3
01:00-02:00AM	1307	35.96	48.8	76.2	80.3	92.0	56.8

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:27/03/12(Tuesday)							
09:00-10:00AM	1286	33.04	47.3	75.0	80.4	92.8	56.6
10:00-11:00AM	1230	34.95	47.2	76.2	79.1	93.3	55.7
11:00-12:00AM	1295	30.50	47.7	75.3	80.6	98.3	57.1
12:00-01:00AM	1265	28.85	51.6	75.4	79.7	95.4	53.9
Date:30/03/12(Tuesday)							
09:00-10:00AM	1325	35.84	55.0	74.8	79.0	94.5	57.5
10:00-11:00AM	1290	31.78	53.3	75.7	80.0	97.4	55.7
11:00-12:00AM	1315	30.41	50.4	74.9	79.5	94.2	53.9
12:00-01:00PM	1245	34.93	48.3	74.2	79.9	94.0	55.8
02:00-03:00PM	1195	36.06	54.7	74.7	80.7	93.6	56.0
03:00-04:00PM	1253	34.39	54.9	75.1	80.3	97.9	55.3

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:31/03/12(Wednesday)							
09:00-10:00AM	1218	32.67	48.6	76.7	79.9	92.5	52.8
10:00-11:00AM	1221	34.31	49.2	75.6	80.4	91.8	56.3
11:00-12:00AM	1270	32.12	48.6	75.2	80.5	92.6	55.1
12:00-01:00PM	1227	33.82	47.1	75.8	80.4	88.9	54.6
02:00-03:00PM	1261	32.51	49.3	74.9	79.6	89.6	57.5
03:00-04:00PM	1205	31.12	46.1	76.3	80.8	96.3	54.6
Date:01/04/12(Thursday)							
09:00-10:00AM	1285	37.19	50.3	75.8	78.9	98.0	56.3
10:00-11:00AM	1255	33.69	51.9	76.3	79.2	96.7	54.4
11:00-12:00AM	1320	34.57	47.1	75.6	79.6	98.8	55.8
12:00-01:00PM	1278	31.84	48.0	74.8	79.4	96.3	56.6
02:00-03:00PM	1246	35.79	50.6	75.4	79.2	98.5	54.8
03:00-04:00PM	1265	36.04	52.4	75.5	78.8	96.4	53.3

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:09/04/12(Monday)							
09:00-10:00AM	1190	34.45	51.6	74.5	78.2	96.2	54.7
10:00-11:00AM	1275	38.82	48.8	74.4	78.6	90.5	53.0
11:00-12:00AM	1238	33.11	53.6	74.6	79.1	96.0	55.0
12:00-01:00PM	1308	35.77	52.9	74.8	79.4	95.7	55.8
02:00-03:00PM	1230	34.39	48.3	75.8	79.7	94.2	53.0
03:00-04:00PM	1266	30.17	52.5	74.9	78.8	94.5	53.1
Date:10/04/12(Tuesday)							
09:00-10:00AM	1184	32.85	51.0	76.5	80.4	95.9	55.5
10:00-11:00AM	1236	29.77	51.3	75.9	80.2	94.5	56.4
11:00-12:00AM	1290	30.07	50.5	75.3	80.4	98.0	58.2
12:00-01:00PM	1216	29.19	51.1	74.8	80.2	92.3	60.2
02:00-03:00PM	1237	33.30	47.8	75.3	79.3	95.4	56.2
03:00-04:00PM	1309	28.86	48.5	74.9	79.8	97.9	54.8

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:11/04/12(Wednesday)							
09:00-10:00AM	1276	31.03	49.4	74.5	79.1	96.6	54.2
10:00-11:00AM	1268	30.40	47.3	75.0	79.8	99.2	54.0
11:00-12:00AM	1242	33.48	48.6	75.8	79.7	99.0	54.8
12:00-01:00PM	1292	32.32	48.1	74.9	79.2	100.0	57.0
02:00-03:00PM	1218	29.78	48.4	76.1	79.7	97.1	55.1
03:00-04:00PM	1328	35.14	47.6	75.6	79.5	99.6	54.9
Date:12/04/12(Thursday)							
09:00-10:00AM	1314	34.56	48.5	74.3	78.9	99.3	56.4
10:00-11:00AM	1252	31.43	49.0	74.6	79.0	98.8	54.4
11:00-12:00AM	1234	32.86	48.8	73.9	78.6	98.2	54.2
12:00-01:00PM	1272	33.38	49.7	74.6	78.8	98.4	54.5
02:00-03:00PM	1248	30.49	50.9	75.8.	79.0	98.5	54.6
03:00-04:00PM	1267	31.78	48.4	75.4	79.4	98.6	53.8

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:13/04/12(Friday)							
09:00-10:00AM	1380	29.94	49.4	75.0	78.6	99.0	54.7
10:00-11:00AM	1295	32.22	47.9	74.9	79.8	99.2	55.7
11:00-12:00AM	1310	31.45	46.8	75.1	79.2	97.9	53.9
12:00-01:00PM	1275	31.68	48.2	74.8	79.1	99.3	54.5
02:00-03:00PM	1285	29.26	50.1	74.0	78.9	98.9	53.8
03:00-04:00PM	1235	36.84	48.2	74.3	78.2	98.5	52.6
Date:14/04/12(Saturday)							
09:00-10:00AM	1295	37.00	48.7	73.9	78.4	99.2	54.0
10:00-11:00AM	1200	39.22	49.4	74.5	78.9	96.6	52.7
11:00-12:00AM	1260	36.82	50.4	74.1	78.9	97.8	53.2
12:00-01:00PM	1180	32.42	48.6	74.8	78.5	99.1	53.8
02:00-03:00PM	1250	33.34	50.2	74.6	79.3	98.8	53.6
03:00-04:00PM	1350	36.54	51.4	75.0	78.6	97.2	53.7

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:15/04/12(Sunday)							
09:00-10:00AM	1340	31.36	51.8	75.9	78.8	95.5	52.2
10:00-11:00AM	1280	28.47	52.0	74.8	78.4	99.0	55.4
11:00-12:00AM	1245	31.46	54.2	74.2	78.5	96.7	53.0
12:00-01:00PM	1240	33.56	49.6	74.6	78.7	97.8	53.6
02:00-03:00PM	1190	35.68	47.4	75.3	78.5	97.4	54.2
03:00-04:00PM	1180	36.78	48.2	74.6	78.4	98.7	53.0
Date:16/04/12(Monday)							
09:00-10:00AM	1235	37.46	49.1	75.4	78.9	98.9	52.6
10:00-11:00AM	1220	35.60	50.2	75.0	78.3	95.4	54.1
11:00-12:00AM	1250	33.68	52.9	74.9	79.0	98.9	54.5
12:00-01:00PM	1260	34.78	54.2	73.9	79.1	97.5	53.7
02:00-03:00PM	1270	31.48	53.4	74.3	78.9	99.0	53.4
03:00-04:00PM	1315	35.68	52.1	74.4	79.3	98.3	54.0

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:17/04/12(Sunday)							
09:00-10:00AM	1165	33.49	48.3	74.1	78.9	96.0	52.4
10:00-11:00AM	1295	37.48	49.0	74.6	78.8	98.6	54.7
11:00-12:00AM	1170	36.57	49.9	74.8	78.6	97.9	52.2
12:00-01:00PM	1225	36.58	50.6	73.9	78.1	98.0	53.2
02:00-03:00PM	1255	36.58	48.7	74.7	79.1	98.2	54.5
03:00-04:00PM	1235	27.45	47.6	74.5	78.4	99.6	52.2
Date:18/04/12(Monday)							
09:00-10:00AM	1240	34.48	48.8	74.5	78.4	97.2	52.3
10:00-11:00AM	1170	36.58	50.1	74.6	79.2	98.4	55.3
11:00-12:00AM	1160	33.76	50.4	74.3	78.6	99.0	53.6
12:00-01:00PM	1178	36.58	49.8	74.8	78.9	96.2	53.3
02:00-03:00PM	1155	35.78	51.4	74.5	79.9	98.6	56.4
03:00-04:00PM	1180	34.96	52.6	74.7	78.5	97.4	53.8

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:26/05/12(Saturday)							
09:00-10:00AM	1308	38.54	48.9	74.4	78.8	99.4	56.2
10:00-11:00AM	1276	30.84	49.0	74.9	79.1	98.4	55.9
11:00-12:00AM	1348	32.58	53.0	74.7	79.2	100.2	56.0
12:00-01:00PM	1295	31.26	51.6	74.1	78.7	99.8	55.2
02:00-03:00PM	1282	32.26	52.8	75.0	79.6	98.5	56.1
03:00-04:00PM	1305	33.48	48.9	74.9	78.9	98.6	53.0
Date:27/05/12(Sunday)							
09:00-10:00AM	1235	34.48	51.0	74.1	79.0	99.5	54.3
10:00-11:00AM	1265	29.64	50.4	74.5	79.4	98.9	55.8
11:00-12:00AM	1245	30.49	47.4	74.3	79.2	100.3	55.4
12:00-01:00PM	1270	31.65	48.9	74.6	78.6	97.0	54.6
02:00-03:00PM	1265	34.76	46.0	75.1	78.9	98.4	55.0
03:00-04:00PM	1240	31.38	48.9	74.8	79.1	98.0	56.8

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:28/05/12(Monday)							
09:00-10:00AM	1238	31.27	46.9	74.2	79.0	96.4	55.0
10:00-11:00AM	1258	30.86	50.3	75.2	78.4	93.4	56.7
11:00-12:00AM	1274	33.58	48.9	74.7	78.9	99.6	53.8
12:00-01:00PM	1300	34.38	46.0	74.9	78.3	100.2	54.9
Date:29/05/12(Tuesday)							
09:00-10:00AM	1250	34.42	49.4	74.6	78.7	95.2	54.7
10:00-11:00AM	1275	32.82	47.6	74.8	78.9	99.7	54.8
11:00-12:00AM	1255	32.26	48.0	74.7	79.7	100.2	56.1
12:00-01:00PM	1285	34.54	46.8	75.5	77.9	98.3	55.6

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:30/05/12(Wednesday)							
09:00-10:00AM	1170	31.61	47.4	74.5	79.4	97.2	53.4
10:00-11:00AM	1240	35.33	45.9	73.9	79.6	100.3	56.3
11:00-12:00AM	1235	33.84	46.8	75.8	79.2	98.7	55.1
12:00-01:00PM	1188	34.45	48.3	75.2	79.3	99.7	53.3
Date:01/06/12(Friday)							
09:00-10:00AM	1170	32.72	50.4	75.5	80.4	97.2	56.8
10:00-11:00AM	1240	33.94	46.7	75.7	80.2	98.0	52.6
11:00-12:00AM	1220	34.13	49.6	76.4	80.3	96.4	54.2
12:00-01:00PM	1265	30.86	47.9	74.3	79.2	97.2	53.4

Time	Traffic Vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				Leq	L_{10}	Lmax	Lmin
Date:02/06/12(Saturday)							
09:00-10:00AM	1245	29.92	47.6	73.5	79.3	97.4	52.9
10:00-11:00AM	1210	30.58	46.8	75.5	78.7	99.3	54.1
11:00-12:00AM	1275	32.48	49.6	74.0	78.1	98.1	53.0
12:00-01:00PM	1190	33.56	47.9	74.0	78.0	97.0	55.3
02:00-03:00PM	1215	34.78	48.8	74.5	79.0	98.8	54.6
03:00-04:00PM	1248	32.67	50.3	74.8	78.4	98.3	55.0
Date:03/06/12(Sunday)							
09:00-10:00AM	1198	33.47	51.2	74.4	78.9	98.1	53.8
10:00-11:00AM	1226	31.39	48.9	74.3	79.7	99.6	55.6
11:00-12:00AM	1264	32.85	47.6	75.5	78.8	97.6	52.9
12:00-01:00PM	1244	33.43	48.4	74.0	79.4	95.8	57.8
02:00-03:00PM	1278	31.93	48.8	75.4	80.2	97.6	53.1
03:00-04:00PM	1304	32.62	49.3	75.2	79.6	95.0	52.3

Summary

Temperature (range): 32-43^0 C

(A) Duration of data collection- 21/03/2012 to 03/06/2012

(B) No. of days ------ 24

(C) 4 hours per day (total days) ------ 5

(D) 5 hours per day (total days) ------ 1

(E) 6 hours per day (total days) ------ 18

(F) Total data collection hours ------ 133

CHAPTER-6

RESULTS AND DISCUSSIONS

6.1 Traffic noise modeling

Artificial Neural Network (ANN) approach has been applied for traffic noise modeling in the present study. The measured parameters were divided into two classes i.e. output parameters (L_{10}, L_{eq})) and input parameters (vehicle volume/hr., percentage of heavy vehicles and average vehicle speed). The input parameters are further divided randomly into three kinds of samples:

1. **Training**: These are presented to the network during training, and the network is adjusted according to its error.
2. **Validation**: These are used to measure network generalization, and to halt training when generalization stops improving.
3. **Testing**: These have no effect on training and so provide an independent measure of network performance during and after training.

A comparison is also made between experimental and ANN output parameters.

In the present study, the multilayer feed forwarded neural network was trained by the back-propagation learning algorithm which is based on gradient descent with momentum weight and bias learning function. The Levenberg-Marquardt optimization technique was used in back-propagation algorithm. The training of a network by back-propagation involves the feed forward of the input training pattern, calculation of back propagation of the associated error and adjustment of weights to minimize the error. The Hyperbolic tangent sigmoid transfer function $\mathbf{F(x) = [(e^x - e^{-x})/ (e^x + e^{-x})]}$ was chosen for hidden layer and linear transfers function $\mathbf{[f(x) = x]}$ for output layer. The performance of the neural network was evaluated in terms of mean square error (MSE) between the targeted output and predicted output for given samples size.

In order to develop a traffic noise prediction model steps given below are followed:

STEP-1. The MATLAB neural network tool box was used for ANN analysis which includes neural network training, testing, performance evaluation and comparison.

STEP-2.ANN Architecture

The prediction accuracy of any neural network is dependent on the number of hidden layer and the numbers of neurons in each layer. So to find out the optimal neural network architecture, in the present case, a number of neural networks architecture have been trained and tested by varying number of neurons in hidden layer.

STEP-3.Training and Testing ANN Architecture

A total of 24 days experimental data sets (samples), including vehicle volume/hr. (Log Q), percentage of heavy vehicles (P), average vehicle speed (Log V), L_{10} , L_{eq} , are randomly distributed for training and testing the ANN model. The network program automatically generates the initial weights and biases which were automatically updated depending upon the error between predicted and targeted output. The program was automatically terminating the training process if any one of the following condition was achieved:

- Maximum Number of epochs
- Error goal achieved
- Minimum gradient reached

Training multiple times will generate different results due to different initial conditions and sampling

STEP-4.Plot the graphs

Regression plot:

- Training
- Validation
- Testing

ANN architecture (3-N-2)

Data Distribution: **Training = 60%**

Validation = 15%

Testing = 25%

NO.OF HIDDEN LAYER NEURONS(N)	CORRELATION COEFFICIENT(R)			MEAN SQUARE ERROR(MSE)		
	Training	Validation	Testing	Training	Validation	Testing
5	0.9342	0.9220	0.9343	0.7081	0.9888	0.6937
6	0.9454	0.9482	0.9202	0.5411	0.5333	0.8232
7	0.9580	0.9653	0.8985	0.4246	0.3325	1.1219
8	0.9560	0.9055	0.9189	0.4316	0.9453	0.7756
9	0.9635	0.8868	0.8903	0.3818	1.0612	1.0562
10	0.9586	0.9427	0.8970	0.4454	0.5580	1.0417
11	0.9377	0.8985	0.9229	0.9473	0.9654	0.9285
12	**0.9434**	**0.9643**	**0.9286**	**0.5641**	**0.4058**	**0.6638**
13	0.9579	0.8777	0.9064	0.4220	1.2652	0.9572
14	0.9402	0.9093	0.9439	0.5725	0.9093	0.5917
15	0.9723	0.9301	0.8826	0.2805	0.7242	1.1575
16	0.9611	0.9179	0.8746	0.3806	0.8303	1.2017
17	0.9519	0.9326	0.8845	0.4978	0.6580	1.2343
18	0.9697	0.9050	0.8669	0.3105	1.0356	1.3347
19	0.9719	0.9151	0.8855	0.2750	1.0117	1.1885
20	0.9711	0.9164	0.8475	0.2964	0.7862	1.5105

21	0.9724	0.8986	0.8361	0.2791	0.9727	1.7108
22	0.9715	0.8974	0.8739	0.3436	1.1300	1.6092
23	0.9408	0.9589	0.8851	0.5835	0.3950	1.2249
24	0.9564	0.9352	0.8942	0.4246	0.6683	1.0463
25	0.9640	0.9309	0.8953	0.5055	0.7916	1.1556
26	0.9654	0.8464	0.8899	0.3328	1.7805	1.1587
27	0.9630	0.9323	0.8986	0.3806	0.6620	0.9870
28	0.9736	0.9112	0.8492	0.2651	1.0223	1.4986
29	0.9423	0.8797	0.8158	0.5920	1.2183	1.8566
30	0.9547	0.8928	0.8681	0.4866	1.1523	1.4531

Comparison of Training, Validation and Testing data for ANN architecture (3-N-2)

The output equation comes out from the ANN is:

Output = 0.87*Target + 9.7

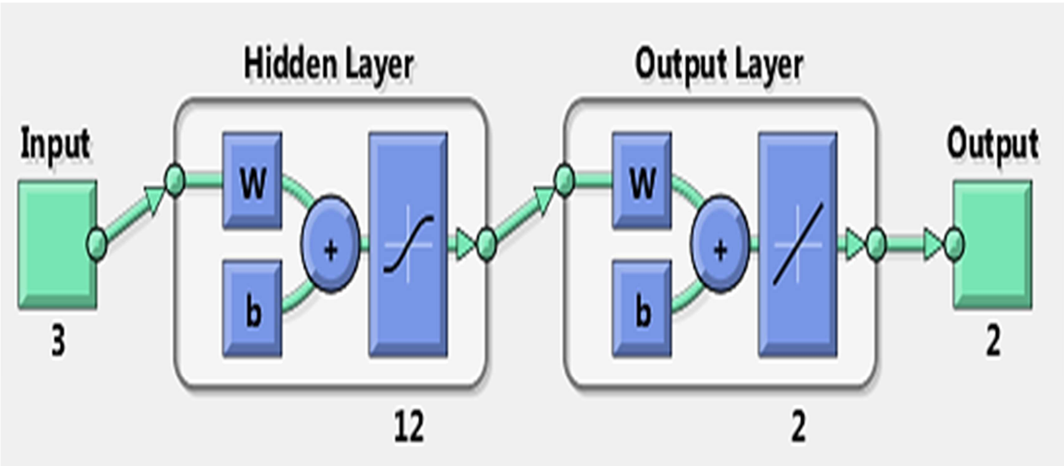

FIG.18 ANN architecture (3-12-2)

W = Weights of connections

b = Bias

ANN OUTPUT & PERCENTAGE ERROR (%)

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
1.	78	80.2	77.56	79.47	0.56	0.90
2.	77.5	79.3	77.12	78.69	0.48	0.76
3.	78.5	80.4	77.995	79.64	0.64	0.93
4.	77.8	79.9	77.38	79.21	0.53	0.85
5.	78	80.2	77.56	79.47	0.56	0.90
6.	76.2	80.8	75.99	79.99	0.27	0.99
7.	76.8	79.6	76.51	78.95	0.36	0.81
8.	76.5	79.8	76.25	79.12	0.32	0.84
9.	77.2	80.7	76.86	79.90	0.43	0.98
10.	76.2	80.3	75.99	79.56	0.27	0.92
11.	76.2	80.8	75.99	79.99	0.27	0.99
12.	75	80.4	74.95	79.64	0.06	0.93
13.	76.2	79.1	75.99	78.51	0.27	0.73

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
14.	75.3	80.6	75.21	79.82	0.11	0.96
15.	75.4	79.7	75.29	79.03	0.13	0.82
16.	74.8	79	74.77	78.43	0.03	0.72
17.	75.7	80	75.55	79.3	0.18	0.87
18.	74.9	79.5	74.86	78.86	0.04	0.79
19.	74.2	79.9	74.25	79.21	-0.07	0.85
20.	74.7	80.7	74.68	79.90	0.01	0.98
21.	75.1	80.3	75.03	79.56	0.08	0.92
22.	76.7	79.9	76.42	79.21	0.35	0.85
23.	75.6	80.4	75.47	79.64	0.16	0.93
24.	75.2	80.5	75.12	79.73	0.10	0.95
25.	75.8	80.4	75.64	79.64	0.20	0.93
26.	74.9	79.6	74.86	78.95	0.04	0.81

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
27.	76.3	80.8	76.08	79.99	0.28	0.99
28.	75.8	78.9	75.64	78.34	0.20	0.70
29.	76.3	79.2	76.08	78.60	0.28	0.75
30.	75.6	79.6	75.47	78.95	0.16	0.81
31.	74.8	79.4	74.77	78.77	0.03	0.78
32.	75.4	79.2	75.29	78.60	0.13	0.75
33.	75.5	78.8	75.38	78.25	0.15	0.69
34.	74.5	78.2	74.51	77.73	-0.02	0.59
35.	74.4	78.6	74.42	78.08	-0.03	0.65
36.	74.6	79.1	74.60	78.51	-0.01	0.73
37.	74.8	79.4	74.77	78.77	0.03	0.78
38.	75.8	79.7	75.64	79.03	0.20	0.82
39.	74.9	78.8	74.86	78.25	0.04	0.69

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
40.	76.5	80.4	76.25	79.64	0.32	0.93
41.	75.9	80.2	75.73	79.47	0.22	0.90
42.	75.3	80.4	75.21	79.64	0.11	0.93
43.	74.8	80.2	74.77	79.47	0.03	0.90
44.	75.3	79.3	75.21	78.69	0.11	0.76
45.	74.9	79.8	74.86	79.12	0.04	0.84
46.	74.5	79.1	74.51	78.51	-0.02	0.73
47.	75	79.8	74.95	79.12	0.06	0.84
48.	75.8	79.7	75.64	79.03	0.20	0.82
49.	74.9	79.2	74.86	78.60	0.04	0.75
50.	76.1	79.7	75.90	79.03	0.25	0.82
51.	75.6	79.5	75.47	78.86	0.16	0.79
52.	74.3	78.9	74.34	78.34	-0.05	0.70

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
53.	74.6	79	74.60	78.43	-0.002	0.72
54.	73.9	78.6	73.99	78.08	-0.12	0.65
55.	74.6	78.8	74.60	78.25	-0.002	0.69
56.	75.8	79	75.64	78.43	0.20	0.72
57.	75.4	79.4	75.29	78.77	0.13	0.78
58.	75	78.6	74.95	78.08	0.06	0.65
59.	74.9	79.8	74.86	79.12	0.04	0.84
60.	75.1	79.2	75.03	78.60	0.08	0.75
61.	74.8	79.1	74.77	78.51	0.03	0.73
62.	74	78.9	74.08	78.34	-0.10	0.70
63.	74.3	78.2	74.34	77.73	-0.05	0.59
64.	73.9	78.4	73.99	77.90	-0.12	0.62
65.	74.5	78.9	74.51	78.34	-0.02	0.70

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
66.	74.1	78.9	74.16	78.34	-0.09	0.70
67.	74.8	78.5	74.77	77.99	0.03	0.64
68.	74.6	79.3	74.60	78.69	-0.002	0.76
69.	75	78.6	74.95	78.08	0.06	0.65
70.	75.9	78.8	75.73	78.25	0.22	0.69
71.	74.8	78.4	74.77	77.90	0.03	0.62
72.	74.2	78.5	74.25	77.99	-0.07	0.64
73.	74.6	78.7	74.60	78.16	-0.002	0.67
74.	75.3	78.5	75.21	77.99	0.11	0.64
75.	74.6	78.4	74.60	77.90	-0.002	0.62
76.	75.4	78.9	75.29	78.34	0.13	0.70
77.	75	78.3	74.95	77.82	0.06	0.61
78.	74.9	79	74.86	78.43	0.04	0.72

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
79.	73.9	79.1	73.99	78.51	-0.12	0.73
80.	74.3	78.9	74.34	78.34	-0.05	0.70
81.	74.4	79.3	74.42	78.69	-0.03	0.76
82.	74.1	78.9	74.16	78.34	-0.09	0.70
83.	74.6	78.8	74.60	78.25	-0.002	0.69
84.	74.8	78.6	74.77	78.08	0.03	0.65
85.	73.9	78.1	73.99	77.64	-0.12	0.58
86.	74.7	79.1	74.68	78.51	0.01	0.73
87.	74.5	78.4	74.51	77.90	-0.02	0.62
88.	74.5	78.4	74.51	77.90	-0.02	0.62
89.	74.6	79.2	74.60	78.60	-0.002	0.75
90.	74.3	78.6	74.34	78.08	-0.05	0.65
91.	74.8	78.9	74.77	78.34	0.03	0.70

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
92.	74.5	79.9	74.51	79.21	-0.02	0.85
93.	74.7	78.5	74.68	77.99	0.01	0.64
94.	74.4	78.8	74.42	78.25	-0.03	0.69
95.	74.9	79.1	74.86	78.51	0.04	0.73
96.	74.7	79.2	74.68	78.60	0.01	0.75
97.	74.1	78.7	74.16	78.16	-0.09	0.67
98.	75	79.6	74.95	78.95	0.06	0.81
99.	74.9	78.9	74.86	78.34	0.04	0.70
100.	74.1	79	74.16	78.43	-0.09	0.72
101.	74.5	79.4	74.51	78.77	-0.02	0.78
102.	74.3	79.2	74.34	78.60	-0.05	0.75
103.	74.6	78.6	74.60	78.08	-0.002	0.65
104.	75.1	78.9	75.03	78.34	0.08	0.70

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
105.	74.8	79.1	74.77	78.51	0.03	0.73
106.	74.2	79	74.25	78.43	-0.07	0.72
107.	75.2	78.4	75.12	77.90	0.10	0.62
108.	74.7	78.9	74.68	78.34	0.01	0.70
109.	74.9	78.3	74.86	77.82	0.04	0.61
110.	74.6	78.7	74.60	78.16	-0.002	0.67
111.	74.8	78.9	74.77	78.34	0.03	0.70
112.	74.7	79.7	74.68	79.03	0.01	0.82
113.	75.5	77.9	75.38	77.47	0.15	0.54
114.	74.5	79.4	74.51	78.77	-0.02	0.78
115.	73.9	79.6	73.99	78.95	-0.12	0.81
116.	75.8	79.2	75.64	78.60	0.20	0.75
117.	75.2	79.3	75.12	78.69	0.10	0.76

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
118.	75.5	80.4	75.38	79.64	0.15	0.93
119.	75.7	80.2	75.55	79.47	0.18	0.90
120.	76.4	80.3	76.16	79.56	0.30	0.92
121.	74.3	79.2	74.34	78.60	-0.05	0.75
122.	73.5	79.3	73.64	78.69	-0.19	0.76
123.	75.5	78.7	75.38	78.16	0.15	0.67
124.	74	78.1	74.08	77.64	-0.10	0.58
125.	74	78	74.08	77.56	-0.10	0.56
126.	74.5	79	74.51	78.43	-0.02	0.72
127.	74.8	78.4	74.77	77.90	0.03	0.62
128.	74.4	78.9	74.42	78.34	-0.03	0.70
129.	74.3	79.7	74.34	79.03	-0.05	0.82
130.	75.5	78.8	75.38	78.25	0.15	0.69

S.NO	RESULTS					
	EXPERIMENTAL		ANN		PERCENTAGE ERROR	
	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)	L_{eq} dB(A)	L_{10} dB(A)
131.	74	79.4	74.08	78.77	-0.10	0.78
132.	75.4	80.2	75.29	79.47	0.13	0.90
133.	75.2	79.6	75.12	78.95	0.10	0.81

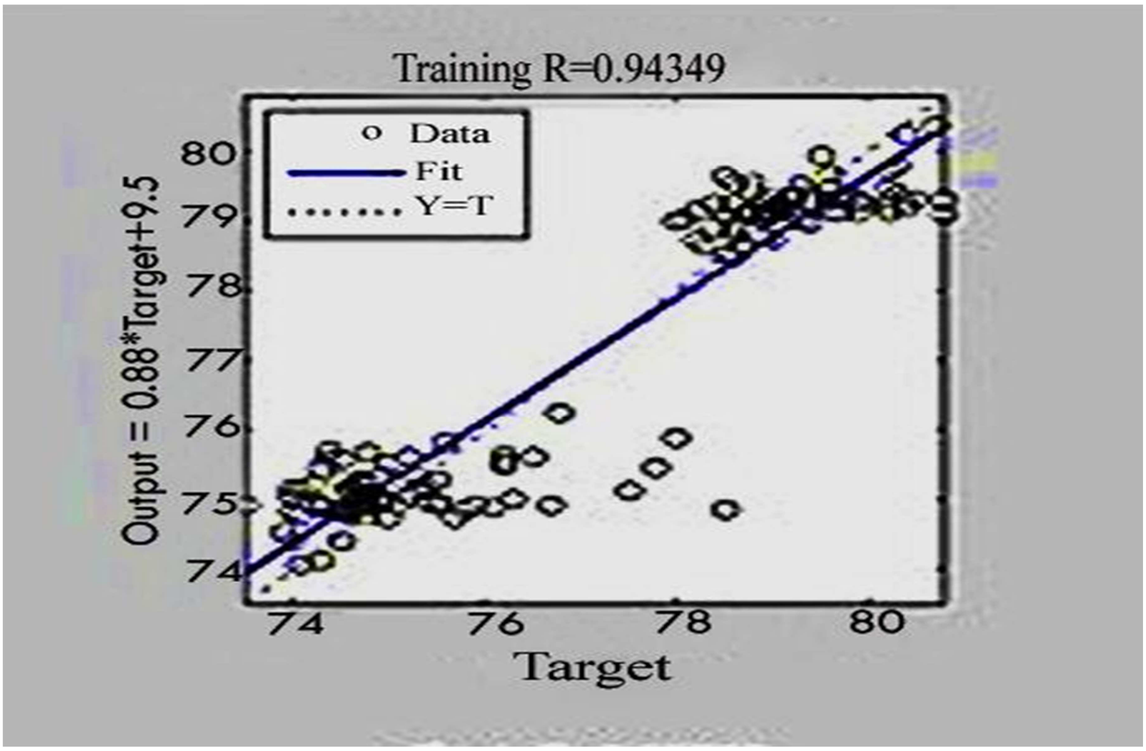

FIG.19 Regression plot for Training set

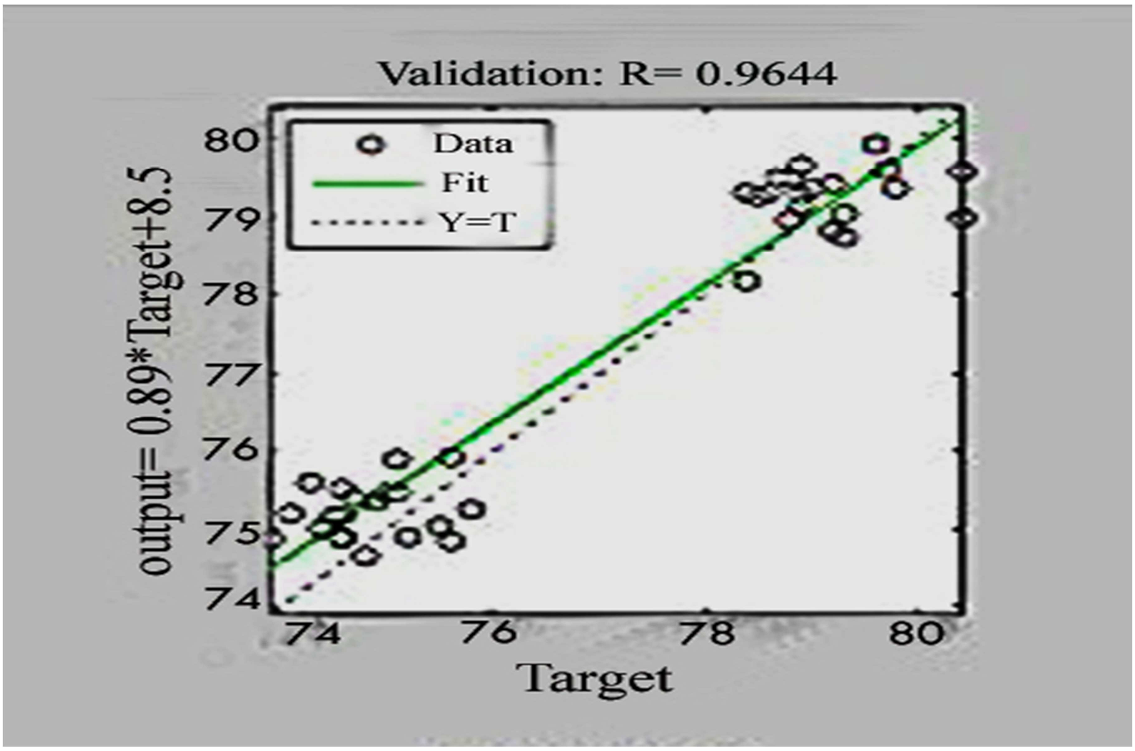

FIG.20 Regression plot for Validation set

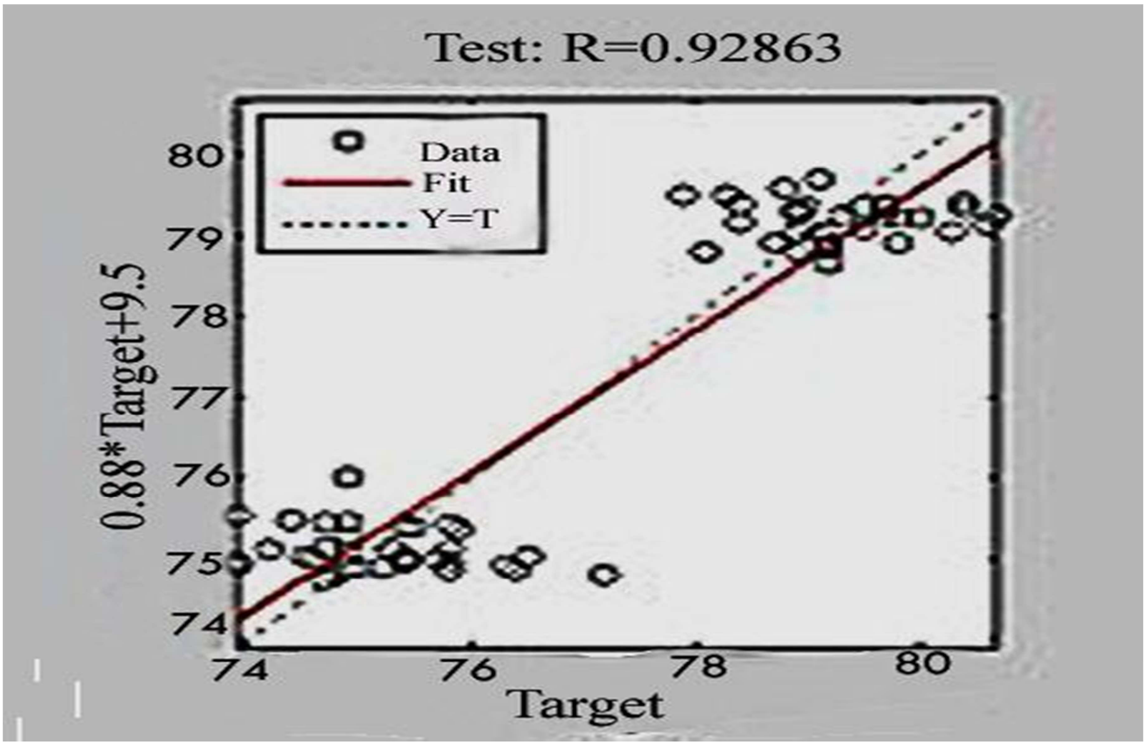

FIG.21 Regression plot for Testing set

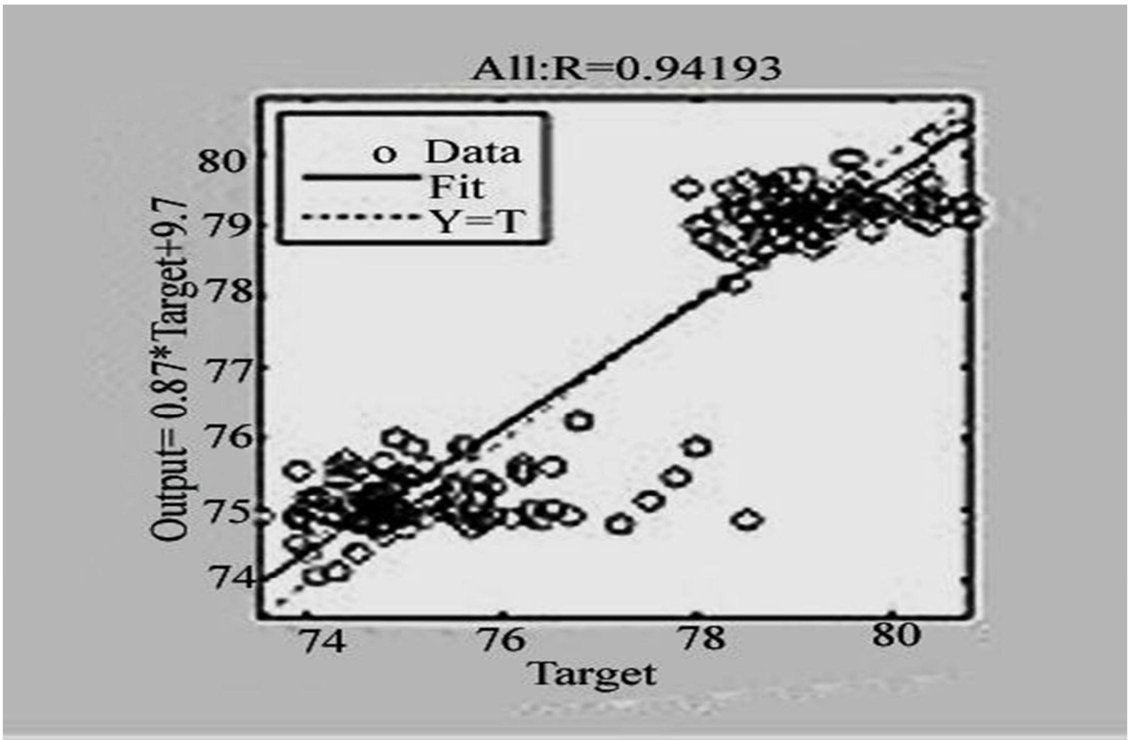

FIG.22 Regression Plot for complete data

FINDINGS

At Patiala-Sangrur Highway (NH-64) following are the findings collected from the above results:

Site measurements findings

1. Leq noise pressure level varied from 73.5 dB (A) to 78.5 dB (A).
2. L10 percentile level varied from 77.9 dB (A) to 80.8 dB (A).
3. Traffic volume varied from 1155 to 1380 Veh/hr.
4. Average vehicle speed varied from 45.0 km/h to 55.0 km/h.
5. The percentage of heavy vehicles varied from 27.45 to 39.73.
6. Lmax noise pressure level varied from 88.9 dB (A) to 100.3 dB (A).
7. Lmin noise pressure level varied from 52.2 dB (A) to 60.2 dB (A).

ANN Findings

1. Leq noise pressure level varied from 73.645 dB (A) to 77.995 dB (A).
2. L10 percentile level varied from 77.47 dB (A) to 79.99 dB(A).
3. Percentage error for Leq varied from -0.19 to 0.64.
4. Percentage error for L10 varied from 0.54 to 0.99.
5. The values of correlation coefficient(R) were 0.9434, 0.9644 & 0.92863 for the training, validation and testing samples respectively.
6. Most of the scatter plots of L10 and Leq vs. Q, P and V were not found to be normal as expected but depend on the amount of data. If there were more data sets in different dates and different locations then better correlation are expected.

CHAPTER-7

CONCLUSION AND FUTURE SCOPE

7.1Conclusion

On the basis of the noise measurements recorded on site and its results that are presented the following conclusions are drawn from the present study:

- Multilayer feed forward back propagation (BP) neural networks were trained and tested by Levenberg-Marquardt (L-M) optimization algorithm to predict L_{10} and L_{eq}, highway noise descriptors with different number of neurons in the hidden layer of the neural network and among all the neural networks tested, one layered neural network architecture 3-12-2 (3-input neurons , 12-neurans in hidden layer and 2- output neurons) was found to be optimum because of better performance in terms of MSE during training, validation and testing in both highway noise descriptors.
- Since the values of correlation coefficient(R) were 0.9434, 0.9644 & 0.92863 for the training, validation and testing samples respectively, and the percentage error varied from -0.19 to 0.64 and 0.54 to 0.99 for Leq and L10, therefore a good correlation coefficient and less percentage error between experimental and predicted output is an indication of better prediction capability of neural network.
- The values of Leq, L10 and Lmax from the highway were observed to be high as per Indian standards therefore remedial measures are essential to reduce its harmful effect.

7.2Future scope

- The present study work does not consider the screening effect of the noise barriers like presence of trees and other vegetation however their presence is quite significant. Therefore study could be made to ascertain the effect of these natural barriers.

- Indiscriminate and heavy horn blowing causes high values of Lmax and consequently affects Leq and L_{10}, hence thorough study of this aspect could be made of this aspect and corrections, if any, be incorporated.
- All the measurements were taken at single location. If different location and timing can be taken then better results can be obtained.
- Vehicle speed was measured manually, but more accurate data can be achieved by using radar gun.
- Three parameters were included heavy vehicle percentage (P), vehicle volume (Q) and vehicle speed. So, more parameter like observer distance, pavement width, surface finish etc. can be included in the prediction and it may give better results.
- It is postulated that a more rigorous approach to matters such as comparison with other techniques would help a clearer picture to emerge as to best practice and future research directions.

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APPENDIX-A

CALCULATION FOR TRAFFIC VOLUME

Date........................

Site: ……………………………………………..

Vehicle Type	Tally Chart			
	Time…..			
Heavy truck (Single-unit truck with 10 wheels)				
Medium truck (Single-unit truck with 6 wheels)				
Buses				
Cars				
Tractors				
3 Wheelers				
2-wheelers (Motor Cycles, Scooters, Mopeds etc.)				

APPENDIX-B

Site: ……………………………………………..

Measurement period: 15 min.

Sound level meter (Microphone):

Distance from Centre of the road (meter)……………………

Height from level of the road (meter) ………………………..

Temperature: ……………….0 C

S.No	Date & Time	Sound pressure level dB (A)			
		Leq	L_{10}	Lmax	Lmin
1.					
2.					
3.					
4.					
5.					
6.					
7.					
8.					
9.					
10.					

APPENDIX-C

OBSERVATION/CALCULATION FOR AVERAGE SPEED

Distance travelled (meters).........

Time in seconds……..

Date/Time	Heavy truck (Single-unit truck with 10 wheels)	Medium truck (Single-unit truck with 6 wheels)	Buses	Cars	Tractors	3 Wheelers	2-wheelers (Motor Cycles, Scooters, Mopeds etc.)