# Noise Impact Assessment and Prediction in Mines Using Soft Computing Techniques

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# Noise Impact Assessment and Prediction in Mines Using Soft-Computing Techniques

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of the requirements for the degree of

## Doctor of Philosophy

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*by*


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*under the guidance of*


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*Dedicated to my Parents*

## National Institute of Technology Rourkela
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# Certificate

This is to certify that the work in the thesis entitled ***Noise Impact Assessment and Prediction in Mines Using Soft-Computing Techniques*** being submitted by ***Santosh Kumar Nanda*** to the National Institute of Technology, Rourkela, Odisha, India, for the award of the degree of Doctor of Philosophy in Engineering, is an authentic record of research work carried out by him under our supervision and guidance and the work incorporated in this thesis has not been, to the best of our knowledge, submitted to any other University or Institute for the award of a degree or diploma.

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# Abstract

Mining of minerals necessitates use of heavy energy intensive machineries and equipment leading to miners to be exposed to high noise levels. Prolonged exposure of miners to the high levels of noise can cause noise induced hearing loss besides several non-auditory health effects. Hence, in order to improve the environmental condition in work place, it is of utmost importance to develop appropriate noise prediction model for ensuring the accurate status of noise levels from various surface mining machineries. The measurement of sound pressure level (SPL) using sound measuring devices is not accurate due to instrumental error, attenuation due to geometrical aberration, atmospheric attenuation etc. Some of the popular frequency dependent noise prediction models e.g. ISO 9613-2, ENM, CONCAWE and non-frequency based noise prediction model e.g. VDI-2714 have been applied in mining and allied industries. These models are used to predict the machineries noise by considering all the attenuation factors.

Amongst above mathematical models, VDI-2714 is simplest noise prediction model as it is independent from frequency domain. From literature review, it was found that VDI-2714 gives noise prediction in dB (A) not in 1/1 or 1/3 octave bands as compared to other prediction models e.g. ISO-9613-2, CONCAWE, OCMA, and ENM etc. Compared to VDI-2714 noise prediction model, frequency dependent models are mathematically complex to use. All the noise prediction models treat noise as a function of distance, sound power level (SWL), different forms of attenuations such as geometrical absorptions, barrier effects, ground topography, etc. Generally, these parameters are measured in the mines and best fitting models are applied to predict noise. Mathematical models are generally complex and cannot be implemented in real time systems. Additionally, they fail to predict the future parameters from current and past measurements.

To overcome these limitations, in this work, soft-computing models have been used. It has been seen that noise prediction is a non-stationary process and soft-computing techniques have been tested for non-stationary time-series prediction for nearly two decades. Considering successful application of soft-computing models in complex engineering problems, in this thesis work, soft-computing system based noise prediction models were developed for predicting far field noise levels due to operation of specific set of mining machinery. Soft Computing models: Fuzzy Inference System (Mamdani and Takagi Sugeno Kang (T-S-K) fuzzy inference systems), MLP (multi layer perceptron or back propagation neural network), RBF (radial basis function) and Adaptive network-based fuzzy inference systems (ANFIS) were used to predict the machinery noise in two opencast mines.

The proposed soft-computing based noise prediction models were designed for both frequency and non-frequency based noise prediction models. After successful application of all proposed soft-computing models, comparitive studies were made considering

Root Mean Square Error (RMSE) as the performance parameter. It was observed that proposed soft-computing models give good prediction results with accuracy. However, ANFIS model gives better noise prediction with better accuracy than other proposed soft-computing models.

***Keywords*:** **Machineries noise; Noise prediction models; Opencast mines, VDI-2714; CONCAWE; ISO 9613-2, ENM; NORDFORSK; VDI-2720; Fuzzy system; Mamdani and Takagi Sugeno Kang (T-S-K) fuzzy inference systems; MLP; RBF; ANFIS; MATLAB**

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*Santosh Kumar Nanda*

# CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# List of Acronyms

| | |
|---|---|
| **SPL** | Sound Pressure Level |
| **SWl** | Sound Power Level |
| **SI** | Sound Intensity |
| **WHO** | World Health Organization |
| **HL** | Hearing Loss |
| **NIHL** | Noise Induced Hearing Loss |
| **SN** | Sensorineural |
| **TTS** | Temporary Threshold Shift |
| **ASHA** | American Speech Language Hearing Association |
| **AAOO** | American Academy of Ophthalmology |
| **ISO** | International Organization for Standardization |
| **B&K** | Brüel & Kjaer |
| **DGMS** | Directorate General of Mines Safety |
| **OCP** | Open Cast Project |
| **SAIL** | Steel Authority of India |
| **BCCL** | Bharat Coking Coal Limited |
| **TISCO** | Tata Iron and Steel Company |
| **CCL** | Central Coalfields Limited |
| **SCCL** | Singareni Collieries Company Ltd |
| **TWA** | Time Weighted Average |
| **HCP** | Hearing Conservation Program |
| **NIOSH** | National Institute for Occupational Safety and Health |
| **PEL** | Permissible Exposure Level |
| **EPPM** | Extended Parallel Process Model |
| **OHS** | Occupational Health and Safety |
| **PPE** | Personal Protective Equipments |
| **NII** | Noise Impact Index |
| **VDI** | Verein Deutscher Ingenieur |
| **CONCAWE** | Conservation of Clean Air and Water in Europe |
| **OCMA** | Oil Companies Material Association |
| **ENM** | Environmental Noise Model |
| **NALCO** | National Aluminium Company Limited |
| **FL** | Fuzzy Logic |
| **FIS** | Fuzzy Inference System |
| **MF** | Membership Function |

| | |
|---|---|
| **COA** | Center of Area |
| **MOM** | Mean of Maximum |
| **SOM** | Smallest of Maximum |
| **LOM** | Largest of Maximum |
| **BOA** | Bisector of Area |
| **MIMO** | Multi Input Multi Output |
| **MISO** | Multi Input Single Output |
| **ANN** | Artificial Neural Network |
| **MLP** | Multi Layer Perceptron |
| **RBFN** | Radial Basis Function Neural Network |
| **ANFIS** | Adaptive Network Based Fuzzy Inference System |
| **LMS** | Least Mean Square |
| **RMSE** | Root Mean Square Error |
| **CPU** | Central Processing Unit |

# CHAPTER 1

# INTRODUCTION

Noise is generated by almost all opencast mining operations from different fixed, mobile and impulsive sources, thereby becoming an integral part of the mining environment. It is defined as sound without agreeable musical quality or as unwanted sound. In opencast mines, noise is a common environmental factor as generated by the heavy earthmoving machineries [1]. The equipment and environment conditions continuously change as the mining activity progresses. Depending on their placement, the overall mining noise emanating from the mining equipment varies in quality and level. In opencast mines most of the mining machineries produce noise levels in the range of 90-115 dBA, exposure to which over long time can result in noise induced hearing loss and other non-auditory health effects in the miners[2, 3].

Hearing loss can impair the quality of life through a reduction in the ability to communicate with each other. Overall, it affects the general health of the human beings in accordance with the World Health Organization's (WHO) definition of health [4, 5]. Hearing loss (HL) can be defined as "the decibel difference between a patient's thresholds of audibility and that for a person having normal hearing at a given frequency" [6].In mining industry, hearing loss or hearing damage is considered as a serious health problem, as reported by various health organizations like the U.S. Environmental Protection Agency (USEPA), the National Institute for Occupational Safety and Health (NIOSH) and the WHO etc. In 1976, a study carried out by the National Institute for Occupational Safety and Health, for coal mining concluded that the coal miners had health conditions worse than the national mean and the hearing damage to coal miners were serious [7].

The impact of noise in opencast mines depends upon the sound power level (SWL) of the noise generators, prevailing geo-mining conditions and the meteorological parameters of the mines. The noise levels need to be studied as an integrated effect of the above parameters. In mining conditions, the equipment conditions and the environment continuously change as the mining activity progresses. Depending on their placement, the overall mining noise emanating from the mines varies in quality and level. Thus, for environmental noise prediction models, the noise level at any receiver point needs to be the resultant sound pressure level (SPL) of all the noise sources. The need for accurately predicting the level of noise emitted in opencast mines is well established. Some of the noise forecasting models used extensively in Europe are those of the German Draft Standard VDI-2714 Outdoor Sound Propagation, Conservation of Clean Air and Water in Europe (CONCAWE) and Environmental Noise Model (ENM) of Australia [8, 9]. These models are generally used to predict noise in petrochemical complexes and mines. These standards or algorithms were proposed in between 1970-1985. Out of these standards, some are not suitable to predict noise accurately as these standards do not take into consideration the attenuations factors such as ground effect, vegetation, barriers, industrial areas etc. To overcome this problem, International Standard Organization (ISO) proposed an empirical noise prediction model in 1996 [10, 11]. The algorithm used in these models relied for a greater part on the interpolation of experimental data which is a valid and useful technique, but their applications are limited to sites which are more or less similar to those for which the experimental data were assimilated.

In the empirical models, nearly all influences are taken into account even when they can not be separately recognized. This is the main advantage of these models. However, the accuracy of these models depends on the accuracy of the measurements, similarities between the conditions where the noise attenuation is analyzed and the conditions where the measurements are carried out, and the statistical method that is used to make the empirical model. The deterministic models are based on the principles of physics of sound and therefore, can be applied in different conditions without affecting the accuracy. But their implementation usually requires a great database of meteorological characteristics such as atmospheric pressure, atmospheric temperature, humidity, wind and so on, which is nearly difficult to obtain. Hence, the implementation of the noise prediction models is usually restricted to the special area where the meteorological data can be available.

All the noise prediction models treat noise as a function of distance, SWL, different forms of attenuations such as geometrical absorptions, barrier effects, ground topography, etc. Generally, these parameters are measured in the mines and best fitting models are applied to predict noise. Mathematical models are generally complex and cannot be implemented in real time systems. Additionally, they fail to predict the future parameters from current and past measurements. It has been seen that noise prediction is a non-stationary process and soft-computing techniques like Fuzzy systems (Mamdani Fuzzy Inference System, Takagi-Sugeno-Kang Fuzzy Inference System), Adaptive neural network-based fuzzy inference systems (ANFIS), Neural networks (Multi-layer Perceptron(MLP), Radial Basis Functions (RBF), Functional Link Artificial Neural Network(FLAN), Neural Fuzzy, PPN) etc. have been tested for non-stationary time-series prediction for nearly two decades. Fuzzy logic was introduced as a mathematical way to represent vagueness in linguistics and can be considered as a generalization of classical set theory. This great innovation has supplemented conventional technologies in many scientific and engineering applications. There is a scope of using different soft computing techniques: Fuzzy systems (Mamdani Fuzzy Inference System, Takagi-Sugeno-Kang Fuzzy Inference System), Adaptive network-based fuzzy inference systems (ANFIS), Neural networks (Multi-layer Perceptron(MLP), Radial Basis Functions (RBF), Functional Link Artificial Neural Network(FLAN), Neural Fuzzy, PPN), etc. for noise prediction in mines.

## 1.1 Research Problem and the Objectives

In this research work, an attempt has been made to propose the appropriate soft computing systems for predicting opencast mining machinery noise. Due to increasing mechanization of mining operations, the noise level in mines have increased over years. To maintain a good working environment, it is important to predict appropriate noise status of machineries in mines. However, the available conventional noise prediction models are mathematically complex and difficult to use. Soft computing based noise prediction models were developed for prediction of the noise of machineries in different opencast mines.

### 1.1.1 The Objectives of the Research Work

- To conduct noise survey in opencast mines to find the noise status of various heavy earth moving machineries.
- To develop both non-frequency and frequency based statistical noise prediction models for prediction of the noise of machineries in different opencast mines.
- To develop noise prediction models using different soft computing techniques viz. Fuzzy Inference Systems (Mamdani, Takagi-Sugeno-Kang Fuzzy Inference System) ii) Multi-layer Perceptron (MLP), iii) Radial Basis Function Network (RBFN) and iv) Adaptive Network based Fuzzy Inference System (ANFIS)etc.
- To develop Fuzzy logic system based noise induced hearing loss prediction models.
- To select and recommend best soft-computing model for noise prediction in opencast mines.

## 1.2 Organization of the Thesis

Seven chapters are presented in this thesis and the structure of organization of the thesis is depicted in Figure 1.1. A chapter-wise summary of the thesis is given below:

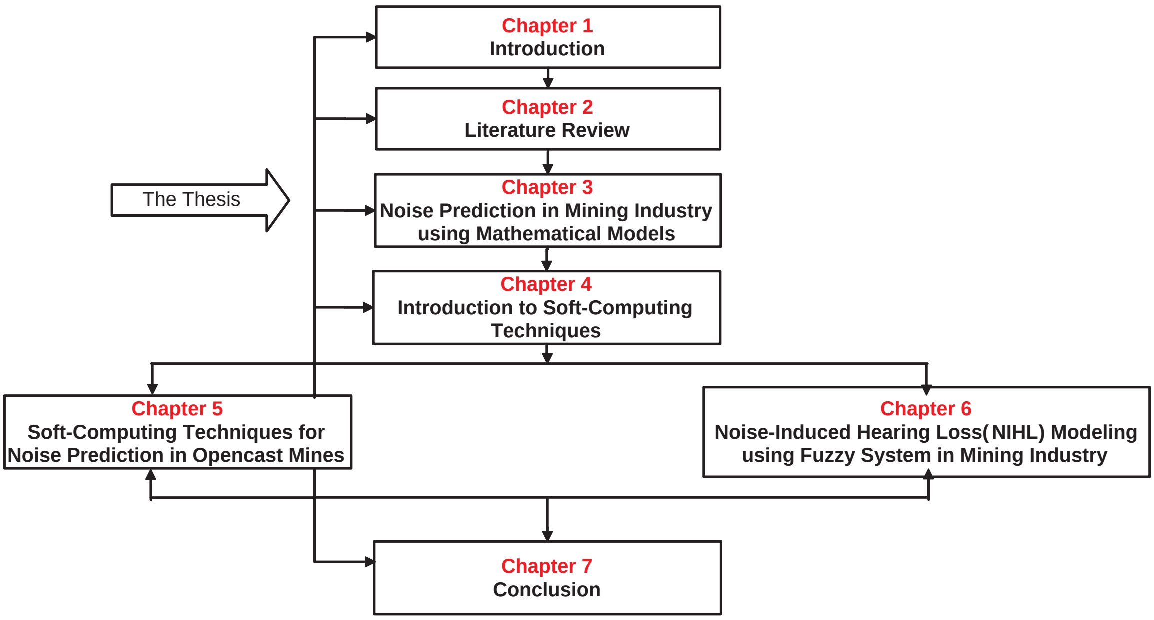



Figure 1.1: Structure of the thesis

- Chapter-2 (Literature Survey and Review)

  This chapter makes a comprehensive review of related literatures to provide background information on the issues to be considered in the thesis and to emphasize the relevance of the present study. This treatise embraces various aspects of prediction of opencast mining machineries noise, noise impact assessment and noise induced hearing loss in mines. The topics included in this chapter for brief reviews are as follows:

  - ⋆ Sources and Types of noise in opencast mines
  - ⋆ Health effect of the noise
  - ⋆ Noise survey in opencast mines
  - ⋆ Survey of noise induced hearing loss in opencast mines
  - ⋆ Noise Impact Assessment
  - ⋆ Noise Prediction Models
  - ⋆ Survey of application of frequency independent (VDI-2714 ) and frequency dependent (CONCAWE, VDI-2720, ISO-9613-2, NORDFORSK etc.) noise prediction models

  - ⋆ Application of soft-computing models (Fuzzy, ANN, RBF etc.) for prediction of noise and noise induced hearing loss

- Chapter 3 (Noise Prediction in Mining Industry using Mathematical Models)
  This chapter highlights the application of mathematical noise prediction models for prediction of opencast mining machineries noise. In this chapter, one frequency independent noise prediction model (VDI-2714) and five frequency dependent noise prediction models were discussed. Location and equipment selection were discussed. Two mines were selected as per the requirement of noise prediction models. The first one is Balaram opencast coal mine of Mahanadi Coalfields Limited (MCL), Talcher (Odisha, India). It was selected for frequency independent models e.x. VDI-2714. The second one is Panchpatmali Bauxite Mine of National Aluminium Company Limited (NALCO), Damanjodi (Koraput, Odisha, India). It was selected for frequency dependent models e.g. CONCAWE , ENM , ISO-9613-2 etc.

- Chapter 4 (Introduction to Soft-Computing Techniques)
  In this chapter, different soft computing techniques were discussed. Soft computing techniques viz. Fuzzy Logic Systems (Mamdani and T-S-K) , Adaptive Network based Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) models, Radial Basis Functions (RBF) etc were discussed. Network architectures, system models, learning algorithm and the procedure for the development of intelligent systems were briefly discussed.

- Chapter 5 (Soft Computing Techniques for Noise Prediction in Opencast Mines)
  This chapter represents the implementation of various soft-computing techniques like fuzzy logic system, neural network, radial basis function network etc. for noise prediction of opencast mining machineries. Due to the high complexity of the classical mathematical models and statistical models (VDI-2714, CONCAWE, ISO-9613-2, ENM etc), the need of implementation of Soft-Computing models in noise prediction obtained greater relevance. In this chapter, two major applications of Soft-Computing models were highlighted. One was for frequency independent noise prediction model (VDI-2714) and the other was for the frequency dependent models viz. CONCAWE, ISO-9613-2, ENM etc.

- Chapter 6(Noise-Induced-Hearing Loss (NIHL) Modeling using Fuzzy Systems in Mining Industry)
  This chapter highlights the application of soft computing techniques for predicting noise induced hearing loss. In this chapter, fuzzy system applications were discussed. Both Mamdani and Takagi-Sugeno-Kang (T-S-K) fuzzy inference systems were applied for predicting noise induced hearing loss. All model results were

highlighted briefly in Chapter 6.

- Chapter 7 (Conclusion)

  This chapter provides a comprehensive summary of the entire research presented in the thesis and clearly outlines the specific conclusions drawn from the work. This is the concluding chapter of the thesis. It presents the major findings of all the studies undertaken and their implications.

## 1.3 Conclusion

Present chapter highlights the importance of noise problem in opencast mines due to increased mechanization. This chapter also develops the new idea of applications of soft-computing models for prediction of the noise from the opencast mining machineries. It also systematically outlines the scope, the motivations behind the research and the objectives of the thesis. In essence, this chapter provides comprehensive outline of the thesis.

# CHAPTER 2

# LITERATURE SURVEY

## 2.1 Introduction

Noise is defined as a sound without agreeable musical quality or as an unwanted sound. It is generated from all the opencast and underground mining operations from almost different fixed, mobile and impulsive sources; thereby becoming an integral part of mining environment. Depending on the sources of generation, noise can be classified into following classes:

- continuous wide band noise,
- continuous narrow band noise,
- impact/impulsive noise,
- repetitive impact noise and
- intermittent noise.

Increased mechanization brought in use of large and high capacity equipments.This increased the magnitude of the problem of noise in mines. Prolonged exposure of miners to high levels of noise can cause auditory and non-auditory health effects. Before initiating any administrative, engineering and medical measures against the noise hazards, noise surveys are essential. They help in identifying the noise pollution sources and quantifying the risk exposure of workers. Effective anti-noise measures can be accordingly formulated and implemented, thereafter [1].

## 2.2 Effects of Noise on Human Health

Exposure to high levels of noise over a long time causes harmful physiological effects. The detrimental effects of noise depend not only on its SPL and frequency, but also on the total duration of exposure and the age, general health and susceptibility of the individual. Harmful effects of noise can be broadly classified into, auditory effects, non-auditory effects and threshold shift [12,13]. Fig. 2.1 represents the noise exposure effects on human health.

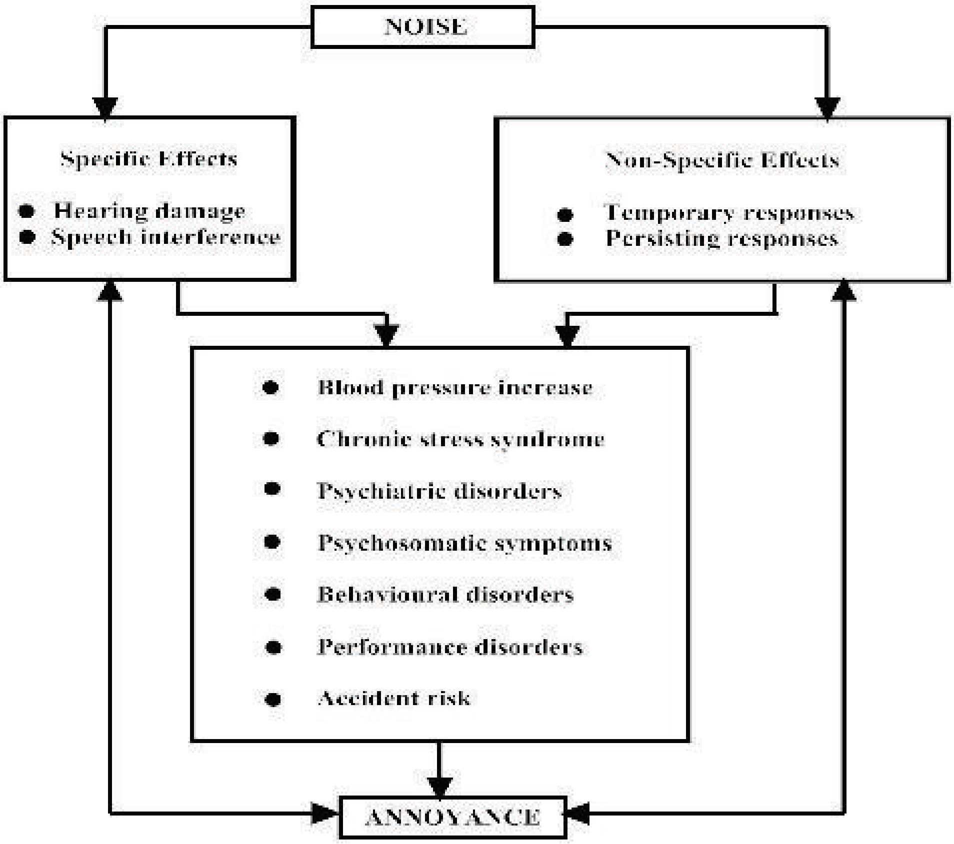



Figure 2.1: Noise exposure effects on human health [13]

## 2.3 Basics of Sound

Sound arises when fluctuations in air pressure give rise to pressure waves which travel through the atmosphere. As they travel they will interact in various ways with their surroundings. Noise is a word which is normally applied to unwanted sound and the sound present in most work situations is unwanted, so it was normally talked about exposure to workplace noise rather than to workplace sound [14,15]. It also defined that smallest audible smallest audible at the frequency of greatest sensitivity in young people with clinically normal ears [16].

### 2.3.1 Sound Pressure Level

Sound pressure is the local pressure deviation from the ambient (average, or equilibrium) pressure caused by a sound wave. Sound pressure can be measured using a microphone in air and a hydrophone in water. The SI unit for sound pressure is the Pascal (symbol: Pa). Sound pressure is used as the fundamental measure of sound amplitude because sound power or sound intensity (energy per unit time and energy per unit area, respectively) are not measurable directly by instruments. However, there are mathematical relationships that relate energy of sound waves and pressure changes. By most instrumentation, sound pressure is measured by providing a reading of root mean square (rms) sound pressure level (Lp) as decibels (dB). Absolute pressure is not measured; instead, the reading is related to a reference pressure. For sound measurement in air the reference pressure is:

- 0.00002 $N/m^2$,
- 20 $pN/m^2$
- 0.0002 $d/cm^2$
- 0.0002 $\mu bar$.

This level was chosen as the normal threshold of hearing for a frequency of 1000 Hz. The sound pressure level is

$$L_p = 20log\frac{(P_1)}{(P_r)} \tag{2.1}$$

or

$$L_p = \frac{10log(P_1)^2}{(P_r)} \tag{2.2}$$

Where $L_p$ = sound pressure level (SPL) (dB), $P_1$ = sound pressure rms, usually in $N/m^2$,$P_r$ = reference sound pressure in $N/m^2$,log = logarithm to base 10. If there are more number of noise sources, then the addition of the SPL is deduced as follows:

$$L_p = 10 \times log\big(10^{\frac{L_1}{10}} + 10^{\frac{L_2}{10}} + 10^{\frac{L_3}{10}} + ....\big) \tag{2.3}$$

similarly, the subtraction of more than two noise sources is calculated as follows:

$$L_p = 10 \times log\big(10^{\frac{L_1}{10}} - 10^{\frac{L_2}{10}} - 10^{\frac{L_3}{10}} - ....\big) \tag{2.4}$$

Here, $L_p$ is used to denote the combined sound levels, while the levels due to each source on its own are denoted by $L_1$, $L_2$, $L_3$ and so on [17–19].

### 2.3.2 Sound Power Level

Sound power is the total amount of sound energy emitted per second by a particular noise source. It is therefore a property of that noise source and will not depend on the environment in which it is placed. In general, it depends on the operating conditions. For example, the noise output of a circular saw will depend on whether it is running freely or being used to cut material. The decibel counterpart of sound power is called sound power level (abbreviated to LW, SWL or PWL) and is the most useful quantity to use when one noise source is compared with another. Use of the term sound power level is preferred, since it characterizes the noise emitted by various types of machines and equipments that are essentially independent of the environments. Sound power level is derived using a reference level.

$$L_W = 10log\frac{(W_1)}{(W_r)} \tag{2.5}$$

where $L_w$ = sound power level (SWL), dB $W_1$ = power of source (watt), $W_r$ = reference power $10^{-l2}$ (w), log = logarithm to base 10.

Under free field conditions, where there are no reflections in sound and sound radiates equally in all directions, the sound propagation wave follows a spherical distribution. The surface area of a sphere, $4\pi r^2$, would be used to define the sphere surrounding a noise source. If sound intensity, defined as the energy per unit area, is multiplied by the surface area, a relationship between sound power and intensity is established:

$$W = IA \tag{2.6}$$

where W = sound power in watt, I= average sound intensity at a distance r from noise source, A = spherical area, $4\pi r^2$ under free field conditions, of an imaginary shell surrounding a source at distance (r) in meter [15, 20, 21].

### 2.3.3 Sound Intensity

Sound intensity is the amount of sound power flowing across a particular imaginary surface with an area of $1m^2$. It is measured in watts per square metre ($Wm^{-2}$). Its decibel counterpart is sound intensity level, and it is measured in some advanced acoustical investigations.From equation 2.6, it is clear that the sound intensity will decrease with the square of the distance. The factor A is reduced as obstructions are introduced. Typically, only half of free field is approached, A is reduced to $2\pi r^2$ for hemispherical radiation. (For 1/4 spherical radiation A = $\pi r^2$; for a spherical radiation A = $\pi r^2/2$.) The sound intensity, like sound pressure and sound power, also covers a large range of values. Sound intensity is expressed as a dB level described by the following relationship [20–22]:

$$L_I = 10logI/I_r \tag{2.7}$$

where $L_I$ = sound intensity level,dB; I = sound intensity at a given distance, $I_r$ = reference sound intensity, $10^{-12}W/m^2$.

### 2.3.4 Relationship between SPL and SWL

For a given set of conditions, sound power and sound intensity can be defined in terms of sound pressure, and vice versa.

$$Sound\ intensity = I = P^2/\rho V \tag{2.8}$$

where P = rms sound pressure (Pa), $\rho$ = density of air at standard conditions 1.2 $kg/m^3$, I = intensity, V = speed of sound in air, 344 m/sec.
Equation 2.8 can be represented in terms of pressure as follows:

$$Sound\ pressure = P = (I\rho V)^{1/2} \tag{2.9}$$

Again Equation 2.8 can be described in terms of intensity.

$$Sound\ power = W = IA \tag{2.10}$$

Using the above equation, the additional relationships exist between sound pressure level and sound power level as:

$$L_w = L_p + 10logA \tag{2.11}$$

A is defined as the surface area of an imaginary shell at distance, r, where Lp would be the measured sound pressure level for any point on the shell [14, 18, 19, 21].

## 2.4 Frequency of Sound

Frequency can be defined as the number of compressions and rarefaction per unit time (set) qualified to a given medium, usually air. Units of frequency are hertz, which designate the number of cycles per second. Frequency is independent of the speed of sound in a given medium. All frequencies travel at the same speed. In air, at standard conditions, all frequencies travel at approximately 344 m/sec. The relationship between the speed of sound and the frequency is defined by:

$$V = \lambda f \tag{2.12}$$

where V = speed of sound (m/sec), $\lambda$ = wavelength (m), f = frequency (Hz).

Wavelength, is defined as the distance a sound wave travels during one pressure cycle (1 compression and 1 rarefaction). The most important frequency for all acoustical measurements is 1000 Hz since this frequency is the reference frequency of the Phon scale i.e. of equal loudness contours, as also it is the base for all series of preferred frequencies. To cover the whole audio range, the scale on both sides of the reference frequency is divided by fractions of octaves like 1/1 octave, 1/2 octave and 1/3 octave etc. The following (Table 2.1) are the preferred frequencies in the octave bands.

Table 2.1: Octave frequency bands

| Centre frequency | Minimum and maximum frequencies |
|---|---|
| 31.5 Hz | 22–45 Hz |
| 63 Hz | 45–89 Hz |
| 125 Hz | 89–177 Hz |
| 250 Hz | 177–354 Hz |
| 500 Hz | 354–707 Hz |
| 1 kHz | 707–1414 Hz |
| 2 kHz | 1414–2828 Hz |
| 4 kHz | 2828–5657 Hz |
| 8 kHz | 5657–11 313 Hz |

In general, in octave band, the center frequency ($f_c$) is related to lower ($f_l$) and upper ($f_u$) band frequency as per the following relation.

$$f_c = \sqrt{f_l f_u} \tag{2.13}$$

Calculation of the band width, $\triangle f$ of every band, using the following equation:

$$\begin{aligned} \triangle f = f_c \frac{2^{1/N} - 1}{2^{2/N}} &= 0.2316 \;\; f_c \;\; for \;\; 1/3 \;\; octave \; band \\ &= 0.7071 \;\; f_c \;\; for \;\; octave \; band \end{aligned} \tag{2.14}$$

For an octave band (1/1), the upper and lower frequencies are related to the center frequency by: $f_l = f_c \ / \ 2^{1/2}$ and $f_u = 2^{1/2} f_c$

For 1/3-octave bands,

$f_l = f_c \ / \ 2^{1/6}$ and $f_u = 2^{1/6} f_c$

1/1 and 1/3 octave bands are used in industrial acoustic measurements and may be used for more accurate noise control work. Narrower bands such as 1/2 octave are used more rarely, particularly to identify prominent tones in a broadband noise [15, 20, 21, 23].

## 2.5 Equal loudness counter and weighting networks

### 2.5.1 Equal loudness counter

The ear is less sensitive to low frequencies than to high frequencies. For example, a 20-Hz tone at 70 dB sounds as loud as a 1000 Hz tone at 40 dB. Equal loudness contours (Figure 2.2) show that as sound levels increase, the ear becomes more uniformly sensitive to all frequencies. In general, an equal-loudness contour is a measure of sound pressure (dB SPL), over the frequency spectrum, for which a listener perceives a constant loudness when presented with pure steady tones. The unit of measurement for loudness levels is the phon and is arrived at by reference to equal-loudness contours. Equal-loudness contours

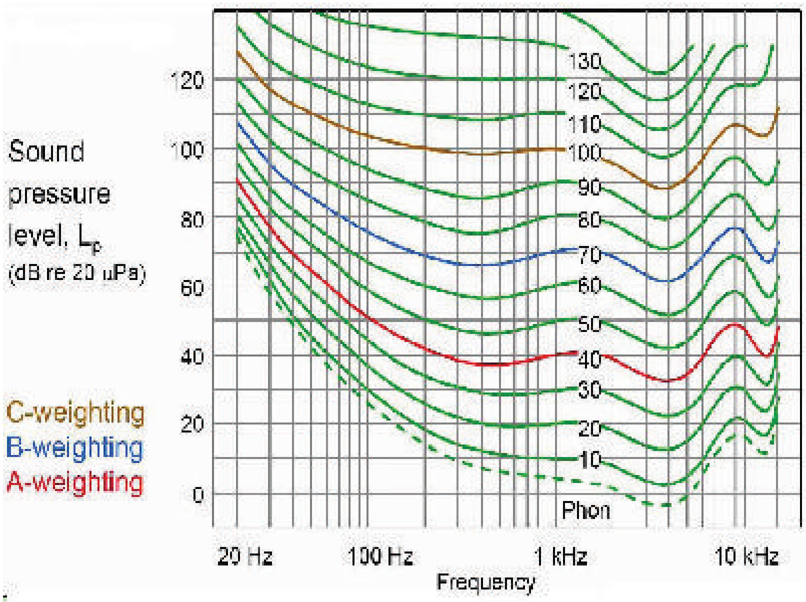



Figure 2.2: Fletcher-Munson equal-loudness counter [21].

are often referred to as "Fletcher-Munson"' curves, after the earliest experimenters, but this is now incorrect, the definitive curves being those defined in ISO:226:2003 [17,20,24].

### 2.5.2 Weighting networks

Loudness of a sound (that is, the subjective response of the ear) varies with frequency as well as with sound pressure and that the variation of loudness with frequency also depends to some extent on the sound pressure. Sound-measuring instruments are designed to make allowances for this behavior of the ear by the use of electronic "weighting" networks. The various standards organizations recommend the use of three weighting networks, as well as a linear (unweighted) network for use in sound level meters. The A-weighting circuit was originally designed to approximate the response of the human ear at low sound levels. Similarly, B and C networks were intended to approximate the response of the ear at levels of 55-85 dB and above 85 dB, respectively. The characteristics of these networks are shown in Figure 2.3. A fourth network, the D-weighting, has been proposed specifically for aircraft noise measurements. However, it has not gained acceptance and the trend appears to be towards the exclusive use of the A-weighting network. Figure 2.3 shows the correction which must be added to a linear reading to obtain the weighted reading for a particular frequency. When even a weighting network proves desirable, in industrial locations, the A-weighting network was taken to measure noise. Table 2.2 represents the A- weighting corrections for different frequency bands [17, 19, 21, 25].

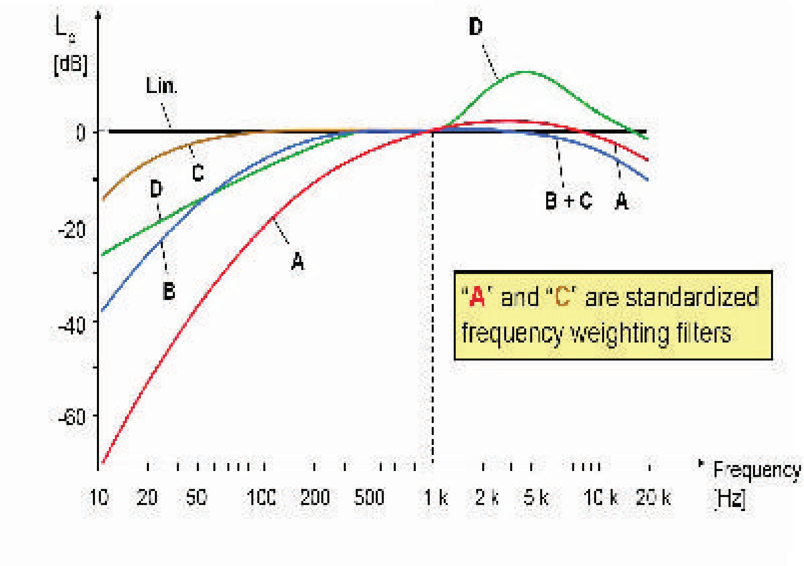



Figure 2.3: International standard A,B and C weighting curves for sound level meters [18].

Table 2.2: A-weighting network corrections (dB) [18]

| Frequency (Hz) | A-weighting correction | Frequency (Hz) | A-weighting correction | Frequency (Hz) | A-weighting correction |
|---|---|---|---|---|---|
| 10 | −70.4 | 160 | −13.4 | 2500 | 1.3 |
| 12.5 | −63.4 | 200 | −10.9 | 3150 | 1.2 |
| 16 | −56.7 | 250 | −8.6 | 4000 | 1.0 |
| 20 | −50.5 | 315 | −6.6 | 5000 | 0.5 |
| 25 | −44.7 | 400 | −4.8 | 6300 | −0.1 |
| 31.5 | −39.4 | 500 | −3.2 | 8000 | −1.1 |
| 40 | −34.6 | 630 | −1.9 | 10000 | −2.5 |
| 50 | −30.2 | 800 | −0.8 | 12500 | −4.3 |
| 63 | −26.2 | 1000 | 0.0 | 16000 | −6.6 |
| 80 | −22.5 | 1250 | 0.6 | 20000 | −9.3 |
| 100 | −19.1 | 1600 | 1.0 | | |
| 125 | −16.1 | 2000 | 1.2 | | |

## 2.6 Mechanism of Hearing

The mechanism of the ear is shown in Fig.2.4. Sound waves from the air around are collected by the *pinna*, travel down the *meatus*, and are conducted to the cochlea via the three auditory ossicles (i.e. the malleus , the incus and the stapes which act as an impedance device, matching the sound wave impedance in the air to that in the basilar fluid) and the oval window. The vibrations conducted in the basilar fluid cause groups of hair cells along the basilar membrane to move; this motion induces piezoelectric action and the mechanical energy is converted to an electrical pulse which travels along the auditory nerve to the brain [26, 27].

The inner ear is highly susceptible to injury and disease. Damage to the inner ear may result in temporary or permanent hearing loss. The auditory nerve attached with cochlea is mostly damaged due to noise.

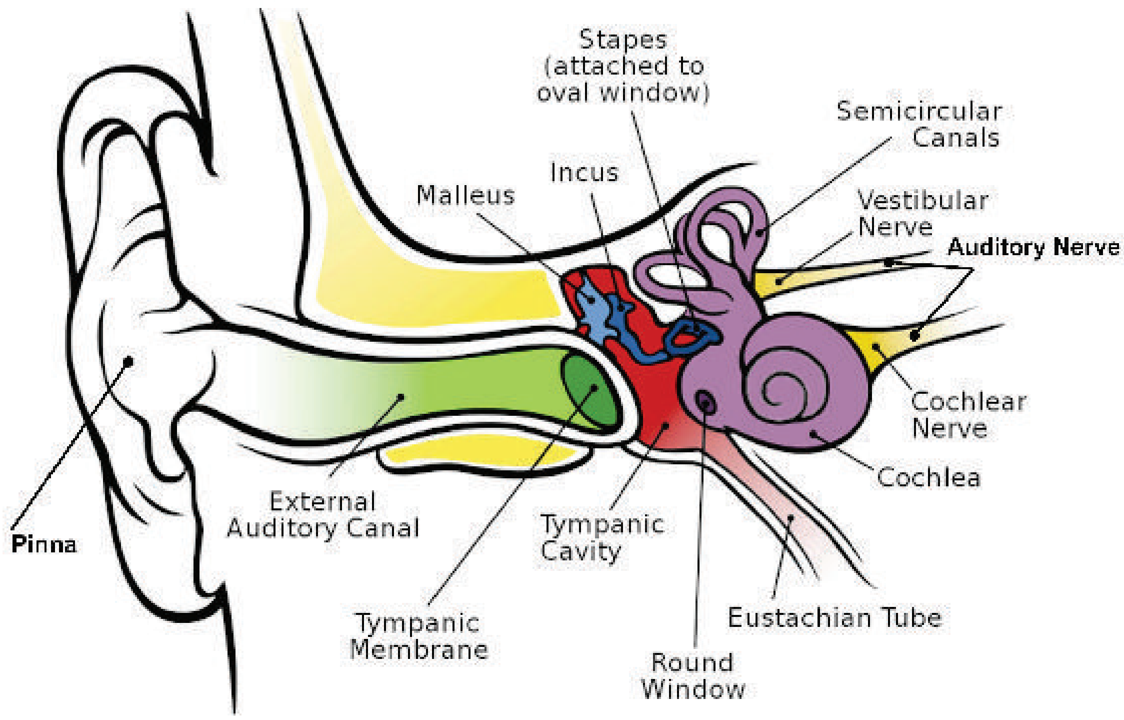



Figure 2.4: Mechanism of human ear, Source [28].

### 2.6.1 Noise Induced Hearing Loss

Hearing loss can impair the quality of life through a reduction in the ability to communicate with each other. Overall it affects the general health of the human beings in accordance with the World Health Organization's (WHO) definition of health [4]. Hearing level (HL) can be defined as "the decibel difference between a patient's thresholds of audibility and that for a person having normal hearing at a given frequency" [29]. Mathematically, it is expressed as:

$$HL = 10 \log I/I_0 \; dB \tag{2.15}$$

where I is the threshold sound intensity for the patient's ear and $I_0$ is the threshold sound intensity for the normal ear.

Hearing loss is mostly of three types:

- Conductive hearing loss
- Sensorineural (SN) hearing loss and
- Mixed hearing loss.

Conductive hearing loss is caused by any disease interfering with the conduction of sound from the external ear to the stapedio-vestibular joints. This type of hearing loss typically results in a loss of sensitivity to air-conducted sound. Conductive hearing losses are usually correctable by medication or surgery. Sensorineural (SN) hearing loss results from non-performance of the lesions of the cochlea (sensory type) and its central connections (neural type). These hearing losses are typically seen as decreased sensitivity to both air- and bone conducted sound. Patients with sensorineural hearing losses may complain of difficulty under hearing noisy situations and sensitivity to loud sounds. In mixed hearing loss, the elements of both conductive and sensorineural deafness are present with in the same ear. There is air-bone gap indicating conductive element and impairment of bone conduction indicating sensorineural loss.

Hearing loss follows chronic exposure to less intense sound than seen in acoustic trauma and is mainly a hazard of noisy occupations [30].

1. Temporary threshold shift (TTS): The hearing is impaired immediately after exposure to noise but recovers after an interval of a few minutes to a few hours.

2. Permanent threshold shift (PTS): The hearing impairment is permanent and does not recover at all.

Hearing handicap is defined as "a binaural average hearing threshold level of greater than 25dB for a selected set of frequencies". In this analysis, the set of frequencies includes (a) 0.5,1 and 2kHz. (b) 1.2, and 3 kHz and (c) 1, 2, 3 and 4 kHz. The 1-4kHz frequency average was recommended by an American Speech-Language-Hearing Association (ASHA) Task Force [31,32], which focused on the need to include frequencies most affected by noise exposure. The ASHA Task force recommended that percentage formulae should include hearing threshold levels for 1, 2, 3 and 4 kHz, with low and high fences of 25 and 75 dB, representing 0 percent and 100 percent hearing handicap boundaries, respectively.

American Academy of Ophthalmology and Otolaryngology (AAOO) Criteria of Hearing loss is shown in the Table 2.3. It indicates the effect of speech communication on hearing loss at 500, 1000 and 2000Hz [1, 33].

Table 2.3: Classes of hearing ability based on average value of hearing levels at 500,1000 and 2000Hz. [1]

| Class | Degree of Handicap | Avrege hearing level, dB | Ability to understand ordinary speech |
|---|---|---|---|
| A | Not significant | <25 | Not significant difficulty with faint speech |
| B | Slight | 25-40 | Difficulty with faint speech |
| C | Mild | 40-55 | Frequent difficulty with normal speech |
| D | Marked | 55-70 | Frequent difficulty with loud speech |
| E | Severe | 70-90 | Shouted or amplified speech only understood. |
| F | Extreme | 90 | Even amplified speech not understood |

The damage caused by noise trauma depends on several factors:

- Frequency of noise : A frequency of 2000 to 3000 Hz causes more damage than lower or higher frequencies;
- Intensity and duration of noise: As the intensity increases, permissible time for exposure is reduced.
- Continuous vs. interrupted noise: Continuous noise is more harmful.
- Pre-existing ear disease.

The audiometric notch was defined when the thresholds at 2000 Hz and 8000 Hz were both minimally at hearing levels 10-dB lower than (better than) the threshold at 4000 Hz. These confirmed that with exposure to broad band, steady noise, or noise with an impulsive component, the first sign was a dip or notch in the audiogram maximal at 4 kHz with recovery at 6 and 8 kHz. The notch broadens with increasing exposure, and may eventually become indistinguishable from the changes of aging (presbycusis), where the hearing shows a gradual deterioration at the high frequencies. Although 4 kHz is the classic frequency affected the notch may be noted elsewhere because the frequency range of the noise influences where the cochlear damage occurs. However, intense low frequency noise may cause maximal loss over the 0.5-2 kHz range and intense high frequency noise loss at 6 or 8 kHz [26, 27].

The audiogram in NIHL shows a typical notch, at 4kHz both for air and bone conduction. It is usually symmetrical on both sides. At this stage, patient complains of high pitched tinnitus and difficulty in day to day hearing. As the duration of noise exposure increases, the notch deepens and also widens to involve lower and higher frequencies. Noise-induced hearing loss is preventable. Persons who have to work at places where noise is above 85dB(A) should have pre-employment and then annual audiogram for early detection. Ear protectors should be used where noise levels exceed 85dB(A) [26, 27, 34].

## 2.7 Noise Measurement

Acoustic instruments have been used for decades to quantify the physical properties of sound and classify them on the basis of physical parameters like amplitude and duration. The instruments are: sound level meter, octave band analyzers, noise dose meter, noise average meter, noise survey meter, statistical analyzers, recorders (magnetic tape, cassette, and pen), acoustic calibrator and sound scope meter. Different weighting networks viz. A, B, and C have been adopted in sound level meters. However, scales other than A are seldom used since they do not provide a good approximation to the human ear frequency response. Noise survey meter is the simplest and cheapest instruments used in the measurement and analysis of steady noise. Sound scope meter is a combination of both sound level meter and octave band analyzer in a small unit. Noise integrator is capable of measuring intermittent noise by giving an intermittent or average noise level when used in conjunction with a noise survey meter. Noise dose meter is used to integrate automatically the sound energy received with regard to its intensity and duration. They are simple, small and assess total noise exposure at work place. The dose may be expressed as a proportion of the maximum permitted 8 hr. dose. Noise measuring instruments of different make and specifications are available in the market, but most widely B & K make instruments are used in practice in view of reliability and accuracy [1].

### 2.7.1 Sound Level Meter

The basic parts of most sound level meters include a microphone, amplifiers, weighting networks, and a display indicating decibels. Schematic diagram of B & K type sound level meter is shown in Figs 2.5. Figure 2.6 shows the block diagram of sound level meter.The microphone acts to convert the input acoustic signal (acoustic pressure) into an electrical signal (usually voltage). This signal is magnified as it passes through the electronic preamplifier. The amplified signal may then be modified by the weighting network to obtain the A-, B-, or C-weighted signal. This signal is digitized to drive the display meter, where the output is indicated in decibels. The display setting may be "fast" response, "slow" response, "impact" response, or "peak" response. Unless one is interested in measuring rapid noise fluctuations, the "slow" response setting is usually used. An output jack may be provided to record or analyze the signal in an external instrument system. Sound level meters are rated in the following categories, based on the accuracy of the meter: (a) type 1, precision; (b) type 2, general-purpose; (c) type 3, survey; and (d) special-purpose sound level meters.

**Class 1:** precision sound level meter, intended for laboratory use or for field use where accurate measurements are required;

**Class 2:** general-purpose sound level meter, intended for general field use and for recording

Most sound level meters have output terminals so that accessories can be attached. These accessories include impact-noise meters, octave-band and octave-band filter sets, graphic recorders etc. Self-contained analyzers are also available, with all components housed in a single unit; that often have variable width settings. Table 2.4 represents the instrument specifications of B&K 2236 sound level meter [18, 19, 24].

Table 2.4: Details of B & K 2236 Sound Level Meter with Octave analyzer [source: B&K 2236 Manual]

| Parameter | Speciation |
|---|---|
| Model | 2236-C |
| Measuring range | 30-140 dB |
| Frequency weighting | A, B, C, D and Linear |
| Filter | (only available with Types 2236 C and 2236 D): Band-pass Filters: Nine 1/1-octave filters at 1/1-octave intervals (base 10) Centre Frequencies: 31.5, 63, 125, 250, 500Hz, 1, 2, 4, 8kHz |
| Frequency Weighting Standards | Selected independently for RMS and Peak RMS: A, C according to IEC651 Type 1 L: flat from 10Hz to 20 kHz ($\pm$ 2 dB) with Type 1 tolerances Peak: C according to IEC651 Type 1 L: flat from 10Hz to 20 kHz ($\pm$ 2 dB) with Type 1 tolerances |
| Time Response | Slow, Fast and Impulse |
| Measuring Mode | Instantaneous ,Max Hold and $L_{eq}$ |
| Output | AC and DC |
| Power Supply | Rechargeable Batteries with Display Facility for their Charge |
| Operating Temperature Range | $0\text{-}50^0$ |
| Display | LCD |
| Physical Characteristics: | Size: $257 \times 97 \times 41$mm Weight: 460g (including batteries) |

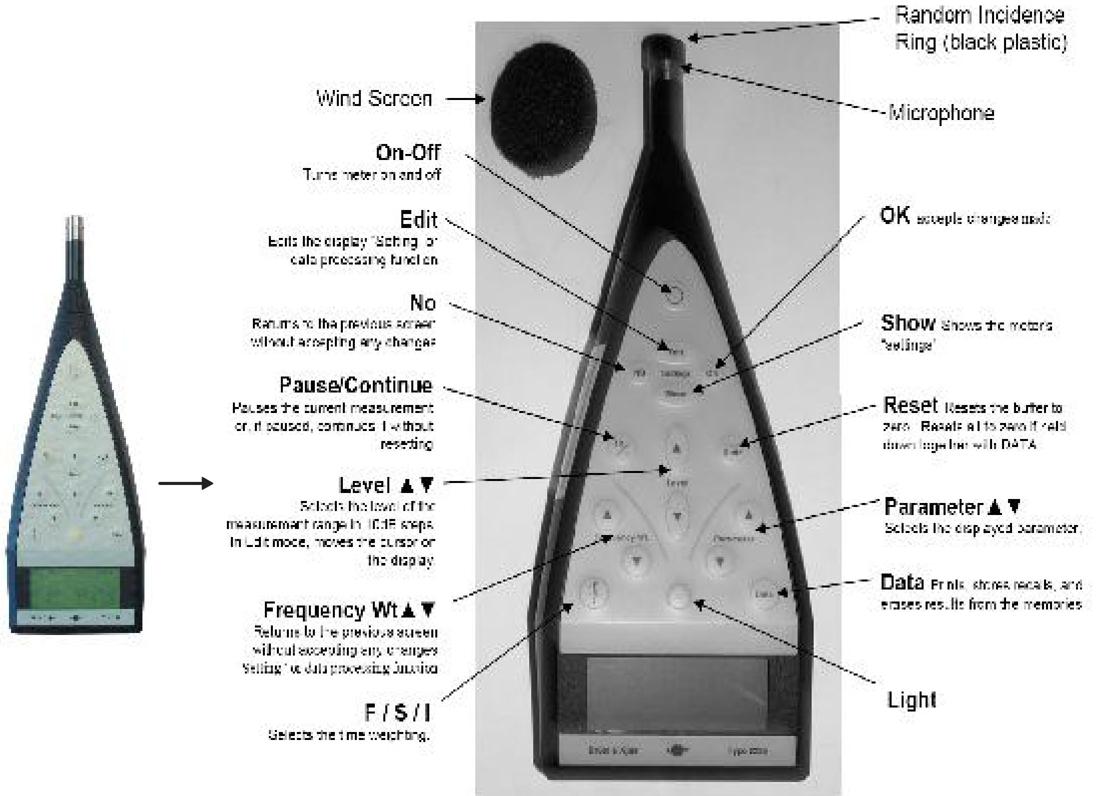



Figure 2.5: Sound Level Meter (B & K 2236) and its Function.

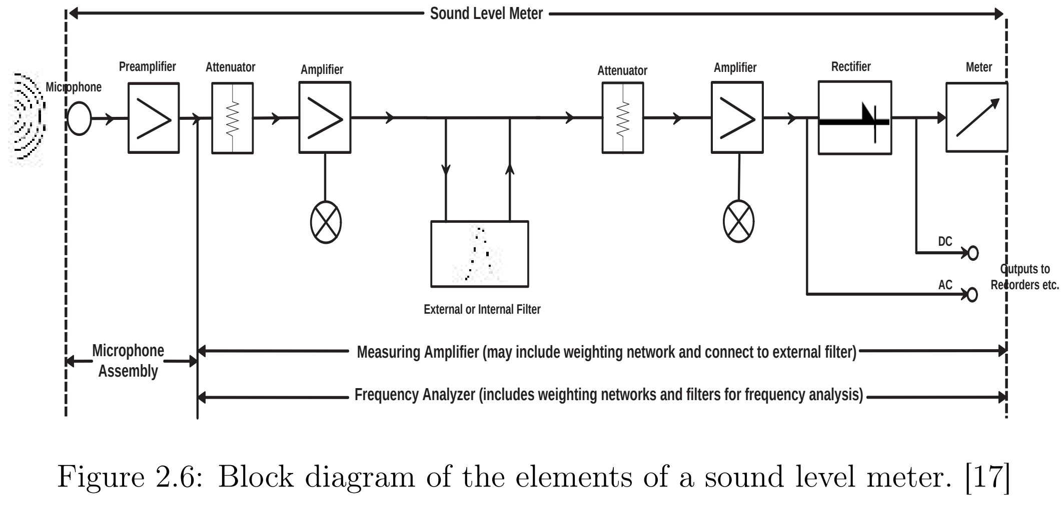



Figure 2.6: Block diagram of the elements of a sound level meter. [17]

## 2.8 Noise Survey in Mines

Noise survey is conducted in mines to determine:

- Ambient noise condition in and around mining complex in 4 cardinal directions.
- Noise levels generated at different locations and from different equipment.
- Systemic octave band analysis for equipment where noise level (Leq) exceeds 90dBA and to know how sound energy is distributed as a function of time.
- Audiometry to know the hearing acuity of workers in the mine (Director General Mines and Safety (DGMS) Circular (Tech.) No.18/1975, No.5, 1990, Circular No.3, 2007)

Noise level should be measured:

- Whenever speech intelligibility is impaired at 0.5m or less. It can be done at the level of the workers head in his ordinary working posture.
- With the microphone 1 m away from the workers head in this position and on both sides.
- It shall be measured when workers complain that they are subjected to uncomfortable noise level.

Marking of risk areas and equipment shall be done do:

- Indicate clearly equipment producing $>$ 85 dB (A)
- Display suitably by sign forbidding entry to all except those wearing appropriate hearing protectors [1].

According to DGMS Technical Circular No. 18 of 1975 and No.5 of 1990 on "Protection of Workers against noise" it is brought to the knowledge of all concerned that Noise is emerging as an important and challenging health hazard for mine workers. In surveys conducted by the DGMS and some other studies, it was found that noise levels in majority of the mining operations were higher than the recommended limit of 90 dB (A) [35].

Utley [36] discussed about the different noise sources available in opencast mines. He stated that in opencast mines, the noise was generated from overburden and coal excavation sites. He concluded that there was insufficient information available to enable a scheme covering all aspects of noise control to be produced.

Singh [37] discussed the environmental impact assessment in mining areas and explained that noise generation from machineries in mines has adverse impacts. The impacts are occupational health hazards, damage to structures, disruption in wild life etc.

He recommended that, due to adverse effect, control of noise in mines is necessary.

Singh [38] discussed on environmental issues with best management practices of responsible mining and gave report on the impact of noise in mining areas. As per his study, the availability of large diameter, high capacity pneumatic drills, blasting of hundreds of tonnes of explosive etc. were identified as noise prone activities. In-pit crushing system with mobile crusher and large capacity materials handling plants were being installed to facilitate speedy handling of large quantities. All these activities were the major sources of noise and vibrations in and around the mining complexes.

Pal and Mitra [39] monitored different noise sources in various opencast mines. They divided noise sources in three classes in open cast project (OCP):(a) operations of heavy machineries/equipment for scraping, dozing, drilling, loading and hauling of the coal and over burden (b) workshop / erection yard activities; and (c) CHP (crusher) operation. They studied the noise level ($L_{eq}$) in day time at OCP. They also illustrated the noise profile of the open cast project and CHP.

Ghose [40] studied the noise pollution in coal mining areas. He discussed about noise mapping, noise measurement and noise analysis. He briefly mentioned noise control in mines.

Bhattacharya et al. [41] did noise survey in Meghatuburu iron ore mine (MIOM) and Sayal coal mine. They monitored the noise levels of equipment used in MIOM and found that the noise level from secondary crusher and drill machines were high. $L_{eq}$ varied between 101 to 106 dB(A) and $L_{max}$ varied between 106 to 110 dBA in frequency range of 250 and 1000 Hz. They also reported the frequency analysis of machineries at two locations of MIOM.

Tripathy and Patnaik [2]reported the effects of noise pollution in an opencast lime stone mine in Orissa. According to them, the audiometric survey at the mine revealed that the employees working more than 21 years developed mild to moderate hearing loss. The following Tables 2.5 - 2.6, show the average threshold level of mine workers in dB in relation to their trade /job.

Khuntia et al. [42] measured noise levels in SAIL mines. They determined the noise dose for different operators in different mines as presented in Table 2.7. The effect of noise on some mine workers of SAIL with age wise, service wise, grade wise, and job wise are illustrated in Tables 2.8-2.11.

Pal and Mitra [43]studied noise pollution in mines and discussed the monitoring procedure and causes of noise pollution in underground mines. According to their report in underground mines the most significant noise sources were the exhaust fan, winding operations, tippler operation and pay loader operations etc. They measured the sound level in mining area (surface) in four directions of each source at different distances such as 5m, 15m, 25 m and so on. They found that in both surface and underground mines,

Table 2.5: Average hearing threshold level of mine workers in dB(A) in relation to their trade/job [2].

| Trade/Job | Hearing Threshold in Speech frequency | | Hearing Threshold in High frequency | | Hearing level at 4000 Hz | |
|---|---|---|---|---|---|---|
| | Lt. ear | Rt. Ear | Lt. ear | Rt. Ear | Lt. ear | Rt. Ear |
| 1.Dozer operator | 22 | 34 | 21 | 24 | 35 | 35 |
| 2. Dumper operator | 23 | 25 | 24 | 28 | 40 | 45 |
| 3. Shovel operator | 34 | 27 | 43 | 41 | 45 | 45 |
| 4. Crusher operator | 26 | 29 | 44 | 46 | 54 | 57 |
| 5. Screen attendant | 32 | 34 | 40 | 39 | 47 | 47 |
| 6. Drill(J/H) operator | 47 | 32 | 63 | 54 | 68 | 68 |
| 7. Compressor operator | 28 | 29 | 45 | 44 | 48 | 53 |

Table 2.6: Average hearing threshold level of mining workers with respect to their period of service (Mine-P) [2]

| Period of service level (years) | Avg. hearing threshold level in speech frequency | | Avg. hearing threshold level in high frequency | | Avg. hearing threshold at 4000 Hz | |
|---|---|---|---|---|---|---|
| | Lt. ear | Rt. ear | Lt. ear | Rt. ear | Lt. ear | Rt. ear |
| 0-10 | 24 | 24 | 25 | 20 | 38 | 25 |
| 11-20 | 30 | 33 | 39 | 41 | 46 | 49 |
| 21-30 | 28 | 28 | 43 | 42 | 51 | 53 |
| $>$ 31 | 44 | 30 | 61 | 51 | 70 | 65 |

the sound pressure level was high and noise control was required in those areas. They proposed some noise control strategies for the noisy sources in mines area.

Pathak et al. [44] described that surface mining noise involved evaluation of sound power levels of the sources and the determination of different attenuation of the acoustic wave during propagation. To evaluate the noise sources within a mine the experimental method developed by them emphasized the determination, of the following:

- Equivalent acoustic centre of different work zones within the mine.
- Ground absorption of sound energy by the type of ground in and around the mines.
- Pit slope attenuation for the prevailing slope conditions within the mine.
- Air absorption of sound during propagation under the predominant meteorological condition.

Mukhopadhyay and Dey [45] in their comprehensive analysis of noise pollution in mines described the 'spherical' and 'hemispherical' propagation of sound. The spherical propagation sound was expressed as $L_w = L_p + 10 \log (4\pi.r^2)$ and the hemispherical

Table 2.7: Calculated noise dose for different operators [42]

| Operations | Mine A | Mine C | Mine D | Mine E |
|---|---|---|---|---|
| | (1) (2) | (1) (2) | (1) (2) | (1) (2) |
| Dumper | 120 91.5 | 58 86.2 | 78 88 | 72 87.5 |
| Drill | 450 100.8 | 90 89.2 | 95 89.2 | 64 87.1 |
| Dozer | — — | — — | 82 88.5 | 120 91.4 |
| Shovel | — — | 70 87.2 | 50 85 | 65 86.7 |
| Crusher | 68 86.2 | 68 86.2 | — — | 61 86.5 |
| Screen | 180 94 | 260 96.8 | — — | 115 91.2 |
| (1) Stands for calculated 8hrs. dose | | | | |
| (2) Stands for equivalent noise exposure level | | | | |

Table 2.8: Hearing loss of employees (age wise) [42]

| Age group | Mine A | | Mine B | | Mine C | | Mine D | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| < 30 years | 1 | 1/– | – | – | 1 | 2/0 | – | – |
| 30-39 years | 2 | 1/1 | 1 | 1/0 | 6 | 4/3 | 2 | 1/1 |
| 40-49 years | 2 | 1/1 | 4 | 3/1 | 3 | 2/1 | 9 | 5/4 |
| 50-58 years | 5 | 2/3 | 14 | 11/3 | – | – | 14 | 8/6 |
| (1) No. of employees examined | | | | | | | | |
| (2) Degree of hearing loss-slight/mild | | | | | | | | |

propagation of sound was $L_w = L_p + 10 \log (2\pi.r^2)$ where 'r' was the radius of the sphere. According to them, the noise can be controlled in mines if the residential colonies and townships could be located reasonably away from the mining premises. Suitable green belt around the mines can attenuate the noise problem. They emphasized that the persons responsible for monitoring noise in the mining environment should be given proper training.

Pal and Saxena [46] reported noise status in some coal mining complexes of Moonidih, Block II and Muraidih mining complex of Bharat Coking Coal Ltd. (BCCL) in Jharia Coalfield, Jamadoda and Sijua group of collieries of (TISCO), North Karanpura and Bhurkunda mining complexes of Central Coalfield Ltd.(CCL) and Godavari Khani complex of Singareni Collieries Company Ltd.(SCCL). The studies included workplace and ambient noise level monitoring, analysis of noise quality and impact assessment (noise indices). Systematic monitoring of noise was carried out in the above mentioned areas using B& K Modular Precision Sound Level Meter (Type-2231) and the noise parameters such as: MaxP, MaxL, MinL, $L_{eq}$ ,and $L_{dn}$were measured /calculated. They found that the ambient noise levels were observed to be exceeding the permissible limits of the day and night times in the residential areas. The Noise Impact Index (NII) for North

Table 2.9: Hearing loss of employees (service wise) [42]

| Age group | Mine A | | Mine B | | Mine C | | Mine D | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| < 1 years | 2 | 2/0 | 0 | 0/0 | 5 | 5/0 | 0 | 0/0 |
| 10-319 years | 3 | 1/1 | 3 | 2/1 | 4 | 2/2 | 4 | 2/2 |
| 20-29 years | – | – | 5 | 5/0 | 2 | 1/1 | 16 | 9/7 |
| 30 years & above | 5 | 2/3 | 11 | 8/3 | – | 0/0 | 5 | 3/2 |
| (1) No. of employees examined<br>(2) Degree of hearing loss-slight/mild | | | | | | | | |

Table 2.10: Hearing loss of employees (grade wise) [42]

| Grade of employees | Mine A | | Mine B | | Mine C | | Mine D | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Non-Skilled | 1 | 1/0 | 1 | 1/0 | 8 | 6/2 | 1 | 1/0 |
| Skilled | 3 | 2/1 | 0 | 0/0 | 2 | 2/0 | 18 | 10/8 |
| High-Skilled | 6 | 2/4 | 16 | 12/4 | 1 | 0/1 | 6 | 3/3 |
| (1) No. of employees examined<br>(2) Degree of hearing loss-slight/mild | | | | | | | | |

Karanpura and Block II/ Muraidih residential complexes were found to be higher than the indicative permissible limits. The investigations have also indicated that the provisions of suitable barriers between the residential areas and the work zones can help in minimizing the noise levels significantly. They also specified the desired width of the green belts for attenuation of noise levels in different locations of coal mining complexes. Most of the mining equipment in the study areas, were observed to be generating noise exceeding the danger limit of 90 dB(A) set by DGMS. Frequency spectrum analysis revealed low frequency dominant noise status for almost all-mining equipment. The noise dose of the operators handling noisy equipment e.g. dozers , dumpers, drills, pay loaders, vibrating/desliming screens, mine exhaust fans, compressors, etc. were observed to be quite high. They also inferred that the status of noise indices of the mining equipment is either poor (Noise index: >0.17-0.34) or very poor (Noise index: 0.0-0.17). Noise index values were considered to be ranging from 0 to 1 with 0 representing very poor i.e. very high nuisance level; where as 1 representing excellent, i.e. zero nuisance level.

Sinha et al. [47] studied noise pollution due to mining activities in Bijolia quarrying site in Rajasthan, India. They carried out noise pollution studies. They found that the noise level was comparatively high in the active zones in the sandstone quarries due to drilling, blasting and the mine service stations. It was found to be in the range of 96 to 125 dB(A). These were much above the limits of 75 dB(A) prescribed by WHO for day

Table 2.11: Hearing loss of employees (job-wise) [42]

| Operators | Mine A | | Mine B | | Mine C | | Mine D | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Dumper | 1 | 0/1 | – | – | 1 | 0/1 | 2 | 1/1 |
| Dozer | 1 | 0/1 | 2 | 2/0 | 1 | 1/0 | 5 | 2/3 |
| Shovel | 1 | 1/0 | 1 | 0/1 | 2 | 2/0 | 5 | 4/1 |
| Drill | 1 | 0/1 | 1 | 0/1 | 5 | 3/3 | 11 | 6/5 |
| Crusher | 4 | 4/0 | 3 | 3/0 | 1 | 1/0 | – | – |
| Screen | 2 | 0/2 | 3 | 3/0 | – | – | – | – |
| (1) No. of employees examined | | | | | | | | |
| (2) Degree of hearing loss-slight/mild | | | | | | | | |

time in industrial areas. They also stated that, in the sandstone quarries the exposure for long periods to these high levels of noise was likely to affect the ear diaphragms of the workers.

United Nations Environment Program [48] discussed the effect and control of noise in Potash mines. According to this report, beneficiation processes generate high levels of noise and vibration, especially during crushing and grinding.

Durr et al. studied on evolution of noise controls of continuous miner conveyer system. For their study, they had chosen Joy 14CM9 continuous miner. The major noise sources on a Joy 14CM9 continuous miner, used for testing, were identified by testing each identified noise source independently. As per their study, they found that the conveyor was the dominant source of noise. The noise level due to the conveyor was affected by the tension in the chain, with higher tensions resulting in higher noise levels. It was also determined that running the conveyor in wet conditions reduced the sound level significantly. They have used urethane coating to treat the conveyor flight bars in order to reduce the impact noise as the bars passed around the conveyor deck. From their study, they concluded that PO#650 urethane coating is the best solution for noise reduction in the continuous miner conveyor system in comparison to the PO#652 urethane coating [49].

Yantek et al. investigated engineering noise controls to reduce sound levels in cabs on air rotary drill rigs at National Institute for Occupational Safety and Health (NIOSH). According to them, the investigation revealed that some drillers are exposed to A-weighted sound levels exceeding 85 dB even though a cab was used. They studied the in-cab sound levels of one such rig. First, preliminary tests were conducted in a controlled environment using accelerometers and microphones with spectral analysis to identify the dominant noise sources for in-cab sound levels. The results indicated that the vibration transmitted from multiple hydraulic pumps to the control panel produced a dominant spike in the sound level spectrum in the 400 Hz 1/3-octave band. Next, field tests were performed in a production environment to evaluate noise controls to reduce in-cab sound levels. They found that utilizing hydraulic noise suppressors reduced the structure borne noise transmitted to the control panel. Further, they concluded that using hydraulic noise suppressors and enhancing soundproofing reduced the in-cab A-weighted sound levels by as much as 4 dB [50].

Gorai and Pal studied noise impact assessment in an iron ore mining residential complex. They have studied in Bailadila iron ore mine, which is situated in the Kirandul village of district Dantewada, India. As per their result, the $L_{dn}$ values for almost all the residential, commercial and sensitive areas were found exceeding the noise standards. In the mining complex, the type IV Double storied colony near "tertiary crushing plant" revealed maximum percentage of highly dissatisfied person (45.71 percent) with maximum $L_{dn}$ values [69.7 dB(A)]. According to them similarly, Nehru colony was found to have minimum percentage of dissatisfied population (8.61 percent) with minimum $L_{dn}$ values [54.8 dB(A)]. The noise impact assessment was carried out by comparing the existing index with the indicative index value. The existing index and indicative index were calculated on the basis of the existing noise levels and the permissible noise levels respectively. They had found that the noise stress of the settlements appeared to be quite high as the existing noise impact index (0.19) was found much higher than that of the indicative noise impact index (0.083) [51].

Vipperman et al. studied noise surveys in coal preparation plants. Their study areas were located in the states of Pennsylvania, Kentucky, Virginia, Illinois, and West Virginia. Their research work consisted of worker dose monitoring, task observations, and equipment noise profiling. The study was covered in eight separate preparation plants. Worker dose monitoring was conducted for three shifts in most cases. Workers experiencing higher than allowable doses were task-observed for one full shift to correlate dose to noise sources. They had also studied noise levels on all floors, and in lunch rooms and control rooms and characterized them. Their results indicated the only workers who routinely spent a significant portion of their shift in the plants away from the control rooms were susceptible to overexposure from noise. Certain pieces of equipment screens, centrifuges and sieve bends are the loudest primary noise sources responsible for the worker noise exposures. As per their study, noise levels and worker noise exposures in eight coal preparation plants were assessed as part of a cross-sectional survey of noise in the mining industry being conducted by NIOSH. Assessment techniques included noise dosimetry, task observations, contour mapping of noise fields, and reverberation time measurements. According to their result, overall noise levels were found to range from 75.9 to 115 dBA throughout the plant. The open construction of the plant provided many direct paths for noise to propagate between floors. Most areas of the plant except control rooms, electrical rooms, and motor control centers were found to have noise levels in excess of 90 dBA, suggesting the noise overexposure will occur if a full 8 h shift was spent within the plant [52].

Camargo et al. [53] studied the noise source identification on a horizontal vibrating screen at NIOSH. According to their study, a cross-sectional survey conducted by the National Institute for Occupational Safety and Health (NIOSH), 43.5 % of coal preparation plant employees are exposed to noise levels that exceed the permissible exposure level (PEL). Furthermore, this study identified the vibrating screen (VS) machines used to separate coal from refuse and water as the main noise contributors in these plants. Their research work presented the results of a study conducted by NIOSH in collaboration with the Acoustical and Vibrations Engineering Consultants Inc, USA. The main goal of their experiments was to identify the dominant noise sources at low frequencies, i.e., from 250 to 1,000 Hz.

Spencer [54] studied the assessment of equipment operators' noise exposure in western underground gold and silver mines in US. According to his study, an assessment of U.S. western hard-rock miners' noise exposures was conducted as part of a multi-year National Institute for Occupational Safety and Health (NIOSH) survey of noise exposures in each sector of the mining industry. His study found high levels of hazardous noise exposure to be common at the sampled U.S. western hard-rock mines, where noise generated by some of the larger hard-rock mining equipment was measured to be in excess of 113 dB(A). Noise from selected mining equipment and operator noise exposures were measured, analyzed, and tabulated for dissemination to the participating sites and were being used to direct NIOSH research and interventions to address the greatest noise hazards. As per his study, eighty-two noise dosimeter measurements were obtained, along with time-motion studies as the miners operated hard-rock mining machines. Ninety-six percent of the operators had daily noise doses that exceeded the Mine Safety and Health Administration's permissible exposure level. The average gold miner dosages while operating the following equipment were: haul trucks - 261%, load-haul-dumps (LHDs) - 235%, single boom drills - 221%, bolters - 214%, and dual boom drills - 163%. The worst exposure level was of a silver miner with a daily dose of 873%.

Roul et al. [55] studied the work place noise status of NALCO Bauxite ore processing plant and found that the level was very high near the secondary crusher operation (98.4 dB(A)) and crusher operation of coal handling plant (104.5 dB(A)). They also found that the Leq levels in all the control room of processing plant were found comfortable where as the same for other locations exceeded the permissible limit. They concluded that the noise control measures were needed to be under taken in order to reduce the emitted sound pressure level of the alarming sound frequencies of each of the noisy equipment.

Pal et al. [56] studied effect of noise on hearing acuity of workers of coal washeries and conducted audiometric analysis. According to them, audiometric analysis serves the following purpose: (a) determining auditory acuity of individuals (b) independent testing of both right and left ears and (c) ascertaining prevailing hearing range from -10 to +90 dB of each subject in different frequency range (from 500 Hz to 8000Hz). They also reported that from the limited audiometric analysis enough conclusion may not be possible to draw, but the nature and magnitude of the problem is really alarming.

Byrne [57] studied hearing loss prevention for mining workers. He evaluated practical technological advances in hearing protective devices for use in different mining environments. According to him, the miners experienced a greater severity of hearing loss than would be expected for non-occupational noise-exposed person of the same age and sex.

Bauer [58] studied noise exposure patterns/sources in various coal mines. According to his study, every day 80% of the miners went to work in an environment where time weighted average (TWA) noise level exceeded 85 dBA and 25% of the miners were exposed to TWA noise level exceeding 90 dBA. He recommended that research was needed to identify mine worker dosage and characterizing of the noisiest equipment and worker activities.

Byrne [59] designed a model hearing conservation program for coal miners, that included both traditional and novel approaches towards hearing loss prevention. The objectives were to design a model HCP (hearing Conservation Program) over 5 year period to demonstrate its efficacy in preventing hearing loss, and transfer finding to the coal mining industry(and others) as quickly and thoroughly as possible.

Kovalchik [60] developed a strategy and implementation plan for utilization of noise controls in mining to reduce noise induced hearing loss (NIHL) among mine workers. According to him, NIOSH analysis of a large sample of audiograms showed that by age 51 about 90% of coal miners and 49% of metal/non metal miners had a hearing impairment. By contrast, only 10% of the non-occupational noise exposed population had a hearing impairment by age 51 and most miners had hearing loss by the time they retired. So he stated that NIHL is the most common occupational disease that is especially acute among miners.

Philips et al. [61] studied the prevention programme for noise and vibration in South African mining industry. Their project included the implemenatation and evaluation of a hearing conservation programme, follow-up of cases of Hand-Arm Vibration Syndrome (HAVS) , development of a rapid diagnostic screening tool for HAVS, investigation of HAVS in a cool mining environment, comparison of the noise and vibration emissions of rock drills, development of best pratice guidelines for whole body vibration and review of the effectiveness of anti-vibration gloves. They also mentioned that the outputs of their projects were designed to assist the industry in achieving the Mine Health Safety Council for a long term SIMRAC programme to reduce NIHL in the work place.

Edwards et al. [62]studied noise exposure levels in South African mining industries. Their noise exposure survey focussed on the large-scale sector of mines (gold, platinum and coal mines) and the small- to medium-scale sector mines (Readymix concrete, sand and aggregate, small and large opencast diamond and large underground diamond mines).Their study achieved the aims of assessing the current noise exposure levels of employees in the mining industries of South Africa, thereby providing a baseline for the evaluation of any future control methods and the facilitation of the prioritizing of necessary control strategies. From their study, they recommended the following: firstly, an integrated and multidisciplinary prevention strategies be implemented to provide a model for individual stake-holders in the industry that could use the information gained from their study as a baseline to measure the success of such prevention strategies. Secondly, it recommended a priori establishment and maintenance of a national database of personal noise exposure that could be accessed from the public domain and by the industry stake-holders.

Kerketta et al. [63]conducted noise monitoring in a Chromite mine, Sukinda Valley, Jajpur District, Odisha, India. They made statistical analysis and found that $L_{eq}$ had greater effect in the evening at the workshop and similarly, the $L_{eq}$ at the air field had greatest effect in the afternoon at 1% level of significance attributed primarily to the heavy traffic density. They concluded that the equivalent noise levels were not the same with respect to the time of day and also at the ambient air quality stations. The $L_{eq}$ level at the workshop , the industrial area, had the greatest effect in the evening. The $L_{eq}$ levels during the time of monitoring did not exceed the prescribed limits at all the locations. They also recommended the following recommendations:

- Because the workshop was one of the most affected industrial areas, the older workers should be regularly changed to work in the less influenced areas to avoid occupational hearing loss.

- Ear protective devices should be worn by all the workers in the work zone areas. In particular, ear protective devices should be required for those working in the workshop.

- For those who primarily work in the work shop, regular use of ear protective devices should be practiced in general and should be mandatory in the evening.

Smith and Sapko [64] determined the extent of the hearing loss hazard from intense noise sources and developed the basic knowledge required to reduce the hazard through effective control technology and training. According to them, impulse noise sources exist throughout the mining and construction industries. There is very little data on blasting in underground complexes, e.g., tunnels and mines. They stated that impulse noise from blasting in an underground mine differs from that on the surface and is strongly influenced by mine geometry, openings, and wall roughness. As per their conclusion, in a mine

Table 2.12: Noise level at survey sites in the mines [65]

| Site | Average noise level (dBA) |
|---|---|
| PIT(drilling machine) | 98 |
| Processing area | 95 |
| Analytical laboratories | 88 |
| Bore hole area | 86 |
| Mess area | 82 |

entry, the peak intensity is higher at a given distance than for the same explosive mass detonated on the surface, with the added complication that significant low frequency acoustic oscillations remain for several seconds after the passage of the pioneer pressure pulse. So the cumulative effect on workers associated with impulse noise exposure of low frequencies remains unclear, although considerable anecdotal evidence suggests that the effect is pronounced.

Amedofu [65] studied the hearing loss of the African gold mine workers. His study determined the impact of hazardous noise on workers and was conducted in a surface gold mining company in Ghana during May-June 2002. The methods used included noise survey, case history, otoscopy and conventional pure-tone audiometry. Five main areas were surveyed for hazardous noise; namely, the pit, processing, the analytical laboratory, the borehole and the mess areas. The results showed that noise levels above 85 dBA occurred in all the above areas except the mess. A total of 252 workers were seen, and out of this number, 59 (23%) had the classical noise-induced hearing loss (NIHL). In addition, NIHL increased as a function of age at 4 kHz and as the duration of exposure increased. It was also noted that out of 81 workers with a pre-employment history of noise exposure, 41 (51%) had NIHL. NIHL varied with regard to job location. 14 (6%) workers had hearing loss greater than 25 dB at the frequencies of speech. Thus, factors not under the control of the company may affect the hearing of an employee. He concluded that the hearing loss varied with the duration of exposure. As such, employees who engage in noisy hobbies or who held noisy second jobs should be encouraged to use effective hearing protection devices during their noise exposure. Company sponsored education programmes should stress the importance of good hearing conservation practices on and off the job, and should also inform employees about other diseases that may affect their hearing. The details of the study are presented in the Tables 2.12-2.14.

Vardhan et al. [3] described the hearing loss of retired mine persons and compared it with hearing of the normal people. They described that those exposed to overall levels of 100 to 120 dB(A) suffered from permanent hearing loss with in a period of several

Table 2.13: Age duration among workers with occupational noise-induced hearing loss [65]

| Worker's age | No.Tested | No.with NIHL | Percent |
|---|---|---|---|
| 20-29 | 70 | 4 | 6 |
| 30-39 | 116 | 25 | 22 |
| 40-49 | 57 | 23 | 40 |
| $50^+$ | 9 | 7 | 78 |
| All age | 252 | 59 | 23 |

Table 2.14: Relationship between duration of noise exposure and noise induced hearing loss (NIHL) (< 25dB HL) [65]

| Duration of exposure (years) | No.Tested | No.with NIHL | Percent |
|---|---|---|---|
| 1-5 | 161 | 29 | 18 |
| 6-10 | 54 | 17 | 31 |
| 11-15 | 27 | 9 | 33 |
| 16-20 | 10 | 4 | 40 |
| All age | 252 | 59 | 23 |

months. The hearing thresholds of retired miners were observed to be higher than the general population.

Johnson et al. [66]used Extended Parallel Process Model (EPPM) to prevent noise induced hearing loss (NIHL) in Appalachia. According to them, using the theoretical model EPPM, when individuals perceive the health threat to serious or severe, they attend to the message and follow the recommended responses. Although the miners recognized hearing loss of perceived susceptibility. Specially those in the mines more than 25 years were not sure whether they could lose more of their hearing (as so much had already been lost). Those with fewer years in the mines, however, were more concerned about hearing protection The Figure 2.7 shows the EPPM model.

Hermanus [67] studied the Occupational Health and Safety (OHS) performance of South African mining sector against the back drop of changes in the composition of the sector, international trends in OHS performance, and the agreement on OHS milestones and targets by mining stake holders at the Mine Health and Safety Summit of 2003. According to him, available data for noise exposure for South African miners suggested that nearly half of these workers more than 10% work in zones in which noise exceeds 85 dB(A) time weighted average, with 11% working in zones in which the noise levels were even higher. There were approximately 4000 cases of noise induced hearing loss in 2004 and approximately 75 million dollars were paid in compensation. As noise levels remain high in the sector and noise abatement interventions were still under development, PPE

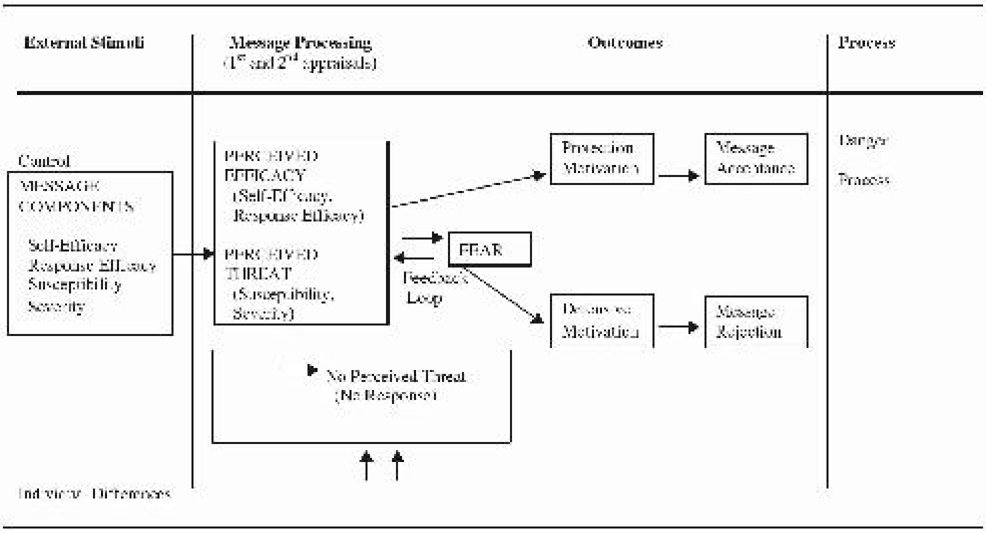



Figure 2.7: Extended Parallel Process Model (EPPM) [66].

(Personal Protective Equipments) were very important in preventing hearing loss . In some working areas, noise levels associated with unlicensed pneumatic drills were so high (in excess of 115 dB) that PPE could also not provide adequate protection.

Joy and Middendorf [68] studied the patterns and trends in noise exposure documented in data collected by Mine Safety and Health Administration inspectors at U.S. coal mines from 1987 through 2004. During this period, MSHA issued a new regulation on occupational noise exposure that changed the regulatory requirements and enforcement policies. The data were examined to identify potential impacts from these changes. The overall annual median noise dose declined 67 % for surface coal mining and 24 % for underground coal mining and the reduction in each group accelerated after promulgation of the new noise rule. According to them the exposure reduction was accompanied by an increase of shift length as represented by dosimeter sample duration. For coal miners exposed above the permissible exposure level, use of hearing protection devices increased from 61 % to 89 % during this period. Participation of miners exposed at or above the action level in hearing conservation programs rapidly reached 86 % following the effective date of the noise rule. Based on the inspection data, the occupational noise regulation appeared to have a strong positive impact on the hearing conservation by reducing exposures and increasing the use of hearing protection devices and medical surveillance.

Kovalchik et al. [69] studied the application of prevention through design for hearing loss in the mining industry. According to their study, National Institute for Occupational Safety and Health (NIOSH) has recognized Noise Induced Hearing Loss (NIHL) as one of the ten leading work-related diseases and injuries in the United States, and has emphasized its importance as one of the critical areas expressed in the National Occupational

Research Agenda. One of the most serious noise problems in the goods producing industries is the operation of continuous mining machines during underground coal mining. In order to minimize occupational hearing loss, noise hazards are "designed out" early in the design process. NIOSH is leading a national initiative called Prevention through Design (PTD) to promote this concept. Their research article described the quiet-by-design approach of a noise control that reduced noise exposures of continuous mining machine operators by 3dB(A) using the four functional areas of PTD, namely Practice, Policy, Research, and Education .Table 2.15 summarized the findings of the research work covered by them.

Table 2.15: Coal miner hearing conservation program enrollment [69]

| Action Level Dose range (%) | Enrollment in HCP | | | | |
|---|---|---|---|---|---|
| | 2000 (%) | 2001 (%) | 2002 (%) | 2003 (%) | 2004 (%) |
| 0-49 | 9 | 68 | 76 | 76 | 77 |
| 50-49 | 7 | 74 | 84 | 85 | 85 |
| 100-149 | 7 | 81 | 91 | 89 | 88 |
| 150-199 | 3 | 77 | 90 | 91 | 89 |
| $> 199$ | 5 | 70 | 87 | 85 | 82 |
| Subtotal $\geq 50$ | 6 | 76 | 87 | 86 | 86 |
| Total | 7 | 73 | 82 | 82 | 82 |

Edwards et al. [70] investigated the feasibility of noise induced hearing loss using Distortion Product Otoacoustic Emission (DPOAE) testing as an adjunct to pure-tone screening audiometry in the annual medical surveillance environment commonly found in the South African platinum mining industry. Signal-to-noise (S/N) ratios of the DPOAE test results conducted at two venues by a trained technician, the degree of hearing loss in platinum employees, the correlation between screening audiometry hearing threshold levels (HTLs) and DPOAE levels, and the ability of the DPOAE test to identify early NIHL in these employees were evaluated. The results of their pilot study provided the scientific evidence that DPOAE testing was feasible for use in a screening audiometry setting by a reasonably trained person. It appeared that the DPOAE testing could provide more information about the actual damage that was occurring in the cochlea if this test format became a regular part of annual medical surveillance testing.

Onder et al. [71] studied Noise Induced Hearing Loss (NIHL)in mines at Turkey. They had applied statistical analysis (hierarchical log-linear) of the data. Data were collected from a quarry and stone crushing screening plant. The mines were located in the eastern part of the Turkey. According to their study, the risky occupation job group of the places surveyed were the drivers and this job group had high possibility of exposure to 70-79 dB(A) noise levels. The drivers, especially of the 46-54 years age group, had experienced NIHL. When the important interactions in the analyses were evaluated, it was found out that 4-11 years experienced crusher workers working in the stone crushing-screening plants had high probability of NIHL because of high exposure to 90-99 dB(A) noise level. Table 2.16 represents their study.

Table 2.16: Information about worker working in the quarry and stone crushing-screening plant [71]

| Worker | Age | Experience | Occupation | Noise level | Hearing loss |
|---|---|---|---|---|---|
| 1 | 53 | 15 | Driver | 70 dB(A) | Yes |
| 2 | 40 | 25 | Crusher worker | 92 dB(A) | Yes |
| 3 | 37 | 18 | Mining machine operator | 79 dB(A) | Yes |
| 4 | 19 | 4 | Mining machine operator | 108 dB(A) | Yes |
| 5 | 31 | 15 | Driver | 70 dB(A) | Yes |
| 6 | 53 | 31 | Driver | 70 dB(A) | Yes |
| 7 | 51 | 31 | Driver | 70 dB(A) | Yes |
| 8 | 29 | 10 | Crusher worker | 92 dB(A) | Yes |
| 9 | 43 | 6 | Driver | 70 dB(A) | Yes |
| 10 | 44 | 27 | Drilling operator | 95 dB(A) | Yes |
| 11 | 48 | 35 | Crusher worker | 92 dB(A) | Yes |
| 12 | 24 | 5 | Crusher worker | 92 dB(A) | Yes |
| 13 | 44 | 3 | Cook | 58 dB(A) | Yes |
| 14 | 18 | 1 | Weigher | 52 dB(A) | No |
| 15 | 39 | 3 | Driver | 70 dB(A) | No |
| 16 | 18 | 1 | Crusher worker | 92 dB(A) | No |
| 17 | 25 | 2 | Worksite chief | 54 dB(A) | No |
| 18 | 29 | 6 | Mining machine operator | 88 dB(A) | No |
| 19 | 23 | 1 | Crusher worker | 92 dB(A) | No |
| 20 | 22 | 1 | Mining machine operator | 88 dB(A) | No |
| 21 | 25 | 4 | Driver | 70 dB(A) | No |
| 22 | 26 | 12 | Mining machine operator | 79 dB(A) | No |
| 23 | 26 | 4 | Drilling operator | 83 dB(A) | No |

Landen et al. [6] made studies to describe workplace noise exposures, risk factors for hearing loss, and hearing levels among sand and gravel miners, and in order to determine whether full shift noise exposures resulted in changes in hearing thresholds from baseline values. They interviewed almost 317 sand and gravel miners regarding medical history, leisure time and occupational noise exposure, other occupational exposures, and use of hearing protection. They conducted audiometric tests performed both before the work shift (following a 12-hour noise free interval) and immediately following the work shift. Full shift noise dosimetry was also conducted. They concluded that, the hearing protection usage was slow, with 48% of subjects reporting that they never used hearing protection. Hearing impairment, as defined by NIOSH was present among 37% of 275 subjects with valid audiograms .

Davies [72] studied the rock drill noise and its effect in trackless mines in South Africa. Trackless mining was first introduced in South Africa in the 1960s in hardrock base-metal mining, mainly at Prieska. In his study, he explained that the manufacturers of rock-drilling equipment had been testing the noise characteristics of their equipment for a considerable time, especially since noise had become a matter for concern. He conducted his tests according to a recognized code, one of which is the CAGI-NEUROP test code3 (Compressed Air and Gas Institute, (USA) and the European Committee of Manufacturers of Compressed Air Equipment).

Pal and Mitra [73] studied the noise pollution and its effects in mines. They found that the noise affected the health of workers and decreased the performance of the workers. The effects of noise in mining industry were expressed in the following manner:

- The main effect of noise on human health is the noise-induced hearing loss or noise deafness. The noise deafness was brought about by the progressive degeneration of the sound sensitive cells of the inner ear. The louder the noise and more often it is repeated, the greater was the damage of hearing. Intermittent noise was more harmful than continuous noise and single very loud noise could damage the ears immediately. Sensitivity of noise varied greatly from person to person. Noise deafness started with the higher frequencies. At first, the worker were unaware of it. They gradually notice their loss of hearing when it begins to involve the lower frequencies. As per NIOSH (National Institute for Occupational Safety and Health, USA) audiometric testing was conducted with respect to the frequencies 1000, 2000 and 3000 Hz (because these were important frequencies for speech perception). As per their study, noise was a function of age, by age 30, about 10% had a hearing loss in excess of 25dB and about 7% exceeding 40dB ; where as by age 50, these figures were much higher, about 50% and about 30% respectively.

- The effect of noise on the efficiency of workers under noisy environment heavily depended on the nature of the task being performed. The more cognitively demanding a task, the more likely it is that noise will adversely affect performance. Table 2.17 shows the effect of noise on performance at various noise level.

They also discussed the permissible noise exposure level as per ISO (International Standard Organization) and OSHA (Occupational Safety and Health Act) standard. Table 2.18 shows the permissible noise standard as per both the standards. In India, the Director General of Mines and Safety (DGMS), in circular no DG (Tech)/18 of 1975, has prescribed the dangerous noise level in mining occupations for workers, from eight hour shift with unprotected ear, as 90 dBA. DGMS also has recommended 115 dB(A) as the noise level at above which an unprotected ear may run a risk of hearing impairment and appropriate ear protective device should be used and 115 dB(A) as the noise level where no workers should enter even with ear protection [73].

Pal and Mitra [74] studied noise pollution status in mines and its effects on the health

Table 2.17: Effect of noise on performance [73]

| Noise level (dB) | Consequence |
|---|---|
| 100 | Serious reduction in alertness, Attention lapses occur, although attention duration is usually not affected. Temporary hearing loss occurs if no protection is provided in the region 600-1200 Hz. Most peoples will consider this level unacceptable, and 8 hour is the maximum duration they will accept. |
| 95 | Considered to the upper acceptance level for occupied areas where people expect the environment be noisy. Temporary hearing loss often occurs in the range of 300-1200 Hz. Speech will be extremely difficult, and people will be required to shout, even through they may be talking directly in to a listener's ear. |
| 90 | At least half of the people in any given group will judge the environment as being too noisy, even through they expected a noisy environment. Some temporary hearing loss in the range of 300-1200 Hz occurs. Skill errors and mental decrements will be frequent. The annoyance factor is high and certain physiological changes often occur. |
| 85 | The upper acceptance level (noise expected) in the range of 150-1200 Hz. Some hearing loss occurs in the range of 300-1200 Hz. This is considered the upper comfort level, although some cognitive performance decrement can be expected, especially where decision making is necessary. |
| 80 | Conservation is difficult i.e. people have to converse in a loud voice less than 30cm (1ft) apart. It is difficult to think clearly after about 1 hour. There may be some stomach contraction and an increase in metabolic rate. Strong complains can be expected from those exposed to this level is confined spaces, and 8h is the maximum duration acceptable within the frequency range 1200-4800 Hz. |
| 75 | To noisy for adequate telephone conservation. A raised voice is required for conversation from 60 cm (2ft) apart. Most people will still judge the environment as being too noisy. |
| 70 | The upper levels for normal conversation, even when conversation are close together (at a distance of 1.83m (6ft) people will have to shout). Although persons such as industrial workers and shipboard personnel who are used to working in a noisy environment will accept that this noise level, unprotect telephone conversation will be difficult (upper telephone level is 68dB). |
| 65 | The acceptance level when people expect a generally noisy environment. Intermittent personal conversation is acceptable. About half of the people in a given population will experience difficulty in sleeping. |
| 60 | The upper limit for spaces used for dining, social conversation, and sedentary recreational activities. Most people will rate the environment as 'good' for general daytime living conditions. |
| 55 | The upper acceptance level for spaces where quite is expected (150-2400 Hz.). People will have to raise their voices slightly to converse over distances greater than 2.44 m. (8ft.). This level of noise will awaken about half of the given population about half of the time. It is still annoying to people who are especially sensitive to noise. |
| 50 | Acceptable to most people where quiet is expected. About 25% will be awakened or delayed in falling sleep. Normal conversation is possible all distances up to 2.44 m. |
| 40 | Very acceptable to all. The recommended upper level for quite living spaces, although a few people may still have sleeping problems. |
| 30 | Necessary for specialized listening tasks (e.g., threshold signal detection). |
| Below 30 | Introduces additional problem, i.e., low-level intermittent sounds become disturbing. Some people have difficulty getting used to the extreme quite and a few may become physiologically disturbed. |

Table 2.18: Permissible noise levels adopted by ISO and OSHA [73]

| Maximum Exposure Time per Working Day, h | Noise level | |
|---|---|---|
| | ISO Code | OSHA code |
| 8 | 90 | 90 |
| 4 | 93 | 95 |
| 2 | 96 | 100 |
| 1 | 99 | 105 |
| 0.5 | 102 | 110 |
| 0.25 | 105 | 115 |

of the workers. According to them, with the increased mechanization in mining industry, noise was an integral part of the mining environment. As equipment became more powerful, noise level generally increased and it had important implications for the worker population. The obvious implication was of course the potential for noise induced hearing loss. In addition, noise produced other health effects like annoyance, fatigue and distraction. These health effects reduced the performance of the workers.

Pal et al. [75]studied the noise status in coal washeries (Eastern region of Jharia coal filed, India) and found that the noise level in side the washeries often exceeded 90dB(A) and occasionally exceeded 100dB(A) which was well above the statutory norms setup by the DGMS and other regulatory agency (ISO code . Thus it carried potential risk of hearing loss to the washery workers. They also identified the noise sources in coal washeies as screen, scraper conveyor , ball mill, crusher, heavy media pump, vacuum pump , rotary breaker and raw coal feeder etc.

Eston et al. [7] studied noise status in Brazilian mining industry. The research work has been conducted by LACASEMIN (Laboratory of Mine Safety and Environmental Control of the Mining Engineering Department of the University of *São Paulo*). In their article, they discussed some International Standards for occupational health issues and mentioned the following:

- In the USA, noise control in the mineral industry effectively started with the Federal Coal Mine Safety and Health Act in 1969. Standards followed the Walsh-Healy criteria summarized in Table 2.19. Such criteria were considered later in the "Federal Metal and Nonmetallic Mine Safety Act".

- In 1977 the Federal Coal Mine Safety and health act defined new standards and rules for metallic and coal mines. Current standards were described in the American code of Federal regulations. Tables 2.20, 2.21 and 2.22 show values by some selected organization.

- Brazilian occupational standard are presented in the "Norma Regulamentadora 15, Anexos 1 e 2", and defined by "Portaria" 3 214 of 08/July/1978. Table 2.23 shows the threshold limit values considered for continuous noise. These values are for general industrial activities and not specifically mining operation.

Table 2.19: Criteria for occupational safety according to the "Walsh-Healy Public Contracts Act" [7]

| Maximum noise level $L_p$ (dBA) | Maximum time exposure (hours) |
|---|---|
| 90 | 8 |
| 95 | 4 |
| 100 | 2 |
| 105 | 1 |
| 110 | 0.5 |
| 115 | 0.25 |

Table 2.20: Occupational Safety and Health Administration - OSHA/USA exposure time for continuous noise. Known as 5 (dBA) rule [7]

| Exposure time (hours) | Maximum level (dBA) |
|---|---|
| 8 | 90 |
| 6 | 92 |
| 4 | 95 |
| 2 | 100 |
| 1 | 105 |
| 0.5 | 110 |
| 0.25 | 115 |

Table 2.21: ISO exposure time recommendations for continuous noise. Limits are followed by several European countries. Known as the 3 dB(A) rule [7]

| Exposure time (hours) | Maximum level (dBA) |
|---|---|
| 8 | 90 |
| 4 | 93 |
| 2 | 96 |
| 1 | 99 |
| 0.5 | 102 |
| 0.25 | 105 |

Murthy et al. [76] studied some noise control techniques for the machineries used in mining industry. They suggested that, noise controls are necessary for the machineries that generate noise level more than 90 dBA because prolonged exposure to excessive noise

Table 2.22: Work place noise levels recommended by OIT- Organization Internationale du Travail. Values are for continuous noise [7]

| |
|---|
| alert limit level : 85 dBA |
| danger limit level: 90 dBA |
| maximum level without ear protection: 115 dBA |
| maximum intermittent noise level : 120 dBA |
| maximum level with protection: 140 dBA |

Table 2.23: Brazilian exposure times according to norm NR 15 from the Labor Department [7]

| Exposure time (hours) | Maximum level (dBA) |
|---|---|
| 8 | 85 |
| 6 | 87 |
| 4 | 90 |
| 2 | 95 |
| 1 | 100 |
| 0.5 | 105 |
| 0.25 | 110 |

could cause permanent damage to hearing. As per their study, there were, two basic rules that must be observed if noise control was to be economic and effective. The first one was to treat the most intense source or component first, since it dominated the overall noise level. Second one is, if a number of sources or components are equally significant, they must all be treated before any reduction was apparent.

Sharma et.al [77] studied the noise status of different machineries that were used in coal industry. They conducted noise survey of different machineries used in opencast, underground mines, coal washeries and coal preparation plant and found that the noise levels were high when compared to accepted limits for occupational noise exposure. Table 2.24, 2.25 and 2.26 show the average noise level outputs of machineries used in coal washeries, coal preparation plants, opencast and underground mines.

They estimated the noise levels of machines used in opencast mining using the following mathematical relationship. In the opencast mining area, noise of different machines could be expressed as:

$$L_p = 20 \log(HP) + KdB \tag{2.16}$$

where HP is the horse power of the machine, K is a factor which depends on the type

Table 2.24: Noise level output of machines in coal washeries and coal preparation plant [77]

| Source | Noise level (dB) |
|---|---|
| Primary crusher | 94 |
| Secondary crusher | 92 |
| Roller crusher | 102 |
| Screening | 99 |
| Ball mill | 96 |
| Jig blower | 104 |
| Coal conveying | 98 |
| Magnetic separator | 96 |
| Magnetic grinding | 96 |
| Vacuum filer | 110 |
| Vibrator | 103 |
| Centrifuge | 103 |
| Tippling | 92 |
| Suction pump | 96 |

Table 2.25: Average noise level of machines in opencast mining [77]

| Source | Noise level dB(A) | |
|---|---|---|
| | Idling | Fully accelerated |
| Shovel | 80 | 97 |
| Dumper | 75 | 92 |
| Bulldozer | 84 | 100 |
| Pay loader | 82 | 100 |
| Drill | 85 | 90 |
| Scraper | 85 | 101 |
| Air compressor | - | 96 |

Table 2.26: Average noise level of machines in underground mining [77]

| Source | Noise level (dBA) |
|---|---|
| Chain and belt conveyor | 88 |
| Drum shearer | 91 |
| Road header | 90 |
| Surface haulage | 94 |
| Transport movement and power loading | 100 |
| Jack hammer drill | 104 |
| Water pump | 97 |

and age of the machine and $L_p$ is the maximum noise level at a distance of 1.5 m from the machine. It is also observed that various types of machines showed higher noise output levels for hours of run. The K factor can be represented by the relation:

$$K = K_0 + 0.00046(NHR)dB \tag{2.17}$$

where NHR is the number of hours run by the machines and $K_0$ has a value of 49. Similar estimate of the maximum noise levels of various machines used in opencast mining could be made based on their horse power and specific number of hours run. The maximum noise level output could be deduced from:

$$L_p = 20\log[0.01x + 10^{4.67}]dB \tag{2.18}$$

where x was the product of machine horse power and number of hours run by machine. As free field condition prevails in open cast mining area, the maximum noise level at any distance from machine could be worked out using the relation:

$$L_w = \overline{L}_p - 10\log(Q/4\pi r^2)dB \tag{2.19}$$

where $L_w$ is the sound power level, $\overline{L}_p$ is average sound pressure level, r is distance of measurement in meter and Q is the directivity factor of the machine. They concluded from their study that the noise level output of machines in opencast mining can be analytically evaluated and the estimated noise level could be in error up to 6dB. This represents a noise error of a factor of 2. There is increase in the noise output of a machine due to higher number of run. The average noise power output of the machines work out to be 113 $\pm$ 3 dB, wherein it is assumed that the machines radiate noise energy uniformly.

Pal et al. [78] studied the role of green belt in noise attenuation in mines. The noise attenuation studies were conducted at two different plantation sites in Singareni Coal field. They concluded that a green belt of more than 30m width was found to be effective for noise attenuation of the order of 5 to 10 dB(A). Vegetation characteristics played an important role. The higher frequencies get attenuated more as compared to the lower frequencies .

Pal and Saxena [79] studied noise impact assessment for coal mining residential complexes. They studied noise impact index in the residential complexes of North Karanpura area, CCL and Block II and Muraidih area of BCCL. They followed the Fractional Impact method which was developed by Schultz in 1982 [80]. This method is based on social survey which leads to the assessment of Sound Level Weighted Population (SLWP), which measures the total number of people expected to be highly dissatisfied by the noise among the entire population. It is expressed as:

$$SLWP = \Sigma[P(L_{dn})_i \times W(L_{dn})_i] \tag{2.20}$$

Where, $P(L_{dn})_i$ = Population distribution function $W(L_{dn})_i$ = weighting function that characterized the severity of the noise impact as a function of day-night sound level ($L_{dn}$). This also takes into account the adverse reaction of the people to noise, which includes speech interference, frustration of the desires for a tranquil environment; and the ability to use telephone, radio and television satisfactorily. Noise impact index (NII) is defined as the SLWP divided by the total population under consideration.

$$NII = \frac{SLWP}{P_{total}} = \frac{\Sigma[P(L_{dn})_i \times W(L_{dn})_i]}{P(L_{dn})_i} \tag{2.21}$$

Applying the expressions 2.20 and 2.21 they found that the status of noise for North Karanpura and Block II/Muraidih residential complexes were found to be higher.

Manoj and Prasannakumar [81] studied the environmental impact assessment of mining activities in magnesite and dunite mine of South-India. In their study, they explained that noise emitted by machines in a mine during drilling, blasting, crushing and loading ranged from 64 dBA to 115 dBA.

Sinha et al. [82] studied noise impact assessment in TISCO mining complexes in Jharia coalfield. The ranking and relative weighting of five important effects of noise exposure were established by them. They also determined the relationship between these parameters and Noise Environment Quality (NEQ) value and accordingly value-function curves for each parameter were developed through Statistical Package (SPSS) for Social Sciences. Then, the resultant NEQ was evaluated for all the residential, commercial and other sensitive areas of the Jamadoba and Sijua complexes of TISCO.

Burger et al. [83] developed a low noise blast hole drilling system to limit the risk of noise-induced hearing impairment in mining operations. In their study they explained that maximum mining workers were exposed with high noise and suffered with hearing loss, and hence this motivated them to design a low noise rock drill for South-African mines. Table 2.27 shows the medical records submitted by South African mines to the Chief Inspector of Mines for the period 1/10/1999 to 30/9/2000. According to their study, the system had to be designed, manufactured, tested and demonstrated in a simulated underground mining environment. The specification required noise levels below 90 dBA. Other important design considerations were ease of manual transport, setting up and operation. The following Tables (2.28, 2.29 and 2.30 )show the details of their study.They concluded that the low noise rock drill developed in this project achieved the noise level specifications required to enable compliance with the applicable legislation.

Table 2.27: Medical records submitted by 189 South African mines to the Chief Inspector of Mines for the period 1/10/1999 to 30/9/2000 [83]

| Disease | Number of cases reported |
|---|---|
| Tuberculosis | 3737 |
| Hearing loss | 3506 |
| Silicosis | 1769 |
| Obstructive airway disease | 161 |
| Asbestosis and pneumoconiosis | 131 |

Table 2.28: Permissible time exposed to various noise level [83]

| Noise level | Maximum exposure per day (hours) | Maximum exposure per week (hours) |
|---|---|---|
| 85 | 8 | 40 |
| 88 | 4 | 20 |
| 91 | 2 | 10 |
| 94 | 1 | 5 |
| 97 | 0.5 | 2.5 |
| 100 | 15 minutes | 75 minutes |

Vardhan et al. [84] studied machine generated noise in opencast mines and found that the noise analysis at different operating conditions of the machine and related that the operators were exposed to high noise level in the frequency range 25Hz to 500Hz when the dumper was moving with load up the gradient and without load down the gradient and the peak noise level occurred at 40 Hz. In case of dozers, the operator's exposure to high noise level occurred at almost all frequencies for operating conditions of the machine. All the drills showed high noise level between 125 Hz and 2000 Hz frequencies and peak noise level at 200Hz and 400Hz frequencies at 3m from the engine (supervisor's position). The excavator showed high noise level at very low frequency, i.e., 25 Hz to 40 Hz. They also explained that there was not much variation in the sound pressure level emitted by machines at 300h, 500h and 700h of maintenance and maximum fluctuation in noise level was obtained at 1000h of maintenance schedule in the frequency range of 25 Hz to 3000Hz for dumpers. The fluctuations could be attributed to two reasons (i)at one thousand hourly maintenance the major noise producing component of the machines were maintained; and (ii) at one thousand hourly maintenance both the three hundred

Table 2.29: Primary noise sources on a rock drill [83]

| Source | Level |
|---|---|
| Valve | 101.5 dBA |
| Exhaust | 122.5 dBA |
| Percussion | 109 dBA |
| Penetration | 114.5 dBA |
| Pawis | 82.5 dBA |
| Mounting | 113.5 dBA |
| Rifle bar | 109.5 dBA |
| Total | 123.5 dBA |

hourly and five hundred hourly maintenance were repeated. This showed that proper maintenance of machines could bring the noise level low considerably there by reducing the operator's exposure to noise.

Vardhan et al. [85] studied the pressure insertion loss of heavy earth moving machinery cabins in opencast mines. The pressure insertion loss of a cabin is defined as the logarithmic ratio between the sound pressure, $P_{source}$ in a point at a certain distance from an acoustic source and the sound pressure $P_{cabin}$ in that same point, when it is enclosed by the cabin, while the acoustic source remains at its same position outside the cabin i.e. Insertion loss = 20 log ($P_{source}$/ $P_{cabin}$). The insertion loss is independent of the position of the measurement point in the lower frequency range (<50 Hz), while at higher frequencies, the insertion loss becomes position dependent.

Gorai et al. [86] studied the workplace noise status of Kotah stone mining complex and found that noise level exceeded 100dB(A) during operating dozer and drilling. Both 35T dumper and shovel (Bucket capacity: 3.2 $m^3$, Diesel Engine:400/330 HP, L & T 300 Front end) operators position were observed on the border line/ slightly exceeded the permissible level of 90 dB (A).

Pal and Saxena [87] studied the societal cost of noise pollution. According to them most of the industrial and developmental activities are supposed to have built-in pollution control and mitigative measures. The society has to essentially bear the cost of various degradation and pollution, directly as well as indirectly. Direct cost being those which the society bears on its own account and the indirect costs are those that the society pays through various taxes, cess. Similarly, noise pollution is supposed to be associated with the following costs :

- Cost of the Health Impacts of the Noise- Exposure to excessive ambient noise levels can cause various health related problems, e.g. sleeplessness, irritation; loss of hearing etc. Taking care of these problems and associated loss in working efficiency puts an extra burden on the society.

Table 2.30: Summary of design parameters for low noise rock drill [83]

| Design Parameter | Value |
|---|---|
| Drilling speed (40 mm drill bit) | > 370 mm / min |
| Maximum air consumption, drill and peripherals | 60 l / min |
| Supplied air pressure | |
| Maximum<br>Maximum | 500 kPa<br>300 kPa |
| Maximum water consumption | 11 l / min |
| Water pressure | > 300 kPa |
| Maximum sound power level | 90 dBA |
| Percussion rate | 40 Hz |
| Thrust needed for drilling | 1570 N |
| Drill steel length | 1.2 - 1.6 m |
| Maximum mass of system | 60 kg |
| Maximum diameter of system | 240 mm |
| Colour | Bright |
| Robust | Drop 1 m onto 50 mm diameter steel rod - drill must still be functional |

- Cost of the Ambient Noise Management in various situations, including sound proofing is directly or indirectly by the society.

Pandey et al. [88] studied dumper operators exposure to noise. The observations indicated that:

- The dumper operators are exposed to occupational noise levels ranging from 85 to 94 dBA during their 8hr daily working shift.
- About 100% dumper operators are exposed to the warning level i.e. 85 dBA.
- More than 46% dumper operators have hearing problems to interfere with their occupational and social activities.
- Dumper operators who had spent more than 9 years in noisy occupations were mostly suffering from hearing loss.
- None of the dumper operators were using hearing protectors. This is probably the most serious reason of noise related hearing loss, fatigue and absenteeism among the dumper operators.

Vardhan et al. [89, 90] studied the noise analysis of heavy earth moving machinery deployed in opencast mines and development of suitable maintenance guidelines for its attenuation. According to them the mining industry in India is facing serious problem of noise due to increasing demand for minerals for which large capacity machines are being deployed producing high noise levels. They studied the daily noise dose and/or noise exposure level of the operators of various types of heavy earth moving machinery and its assessment, noise characteristics at different operating conditions of the machine.

Vardhan et al. [91] investigated the principal sources of sound from heavy earth-moving machinery, namely a bulldozer and a front-end loader. They have found that the major sound sources were the exhaust and air inlet for the engines and the engine cooling fan on the bulldozer. Sound from the exhaust was an important source at nominal one-third-octave midband frequencies from 25 Hz to 250 Hz; sound from the air inlet was a significant contributor in the range of midband frequencies from 25 Hz to 500 Hz. Cooling fan noise for the bulldozer was important in the frequency range from 315 Hz to 3150 Hz. According to them, for the front-end loader, the enclosed cab in which the operator sits provided good noise reduction at frequencies greater than 400 Hz up to 20 kHz. Examination of the spectrum of the sound produced by these and other heavy earth-moving machines can indicate the need for maintenance efforts to restore noise-control capabilities that were originally installed or which should be installed.

Gorai et al. [92] studied the status of workplace noise in the Bailadila iron ore mining complex, India. They found that the high workplace noise situation cause severe harmful consequences to the exposed workers in long run. The noisy equipment/installations in the mine are the operations of Ingersoll-Rand and Wagon drill machine, dozer, dumper-shovel combination, crushing plant, etc.

Ramlu [93]discussed the occupational noise exposure and hearing damage in mining industries. According to him use of various noisy equipments used in industrial plants particularly in heavy industries like mining, civil construction, iron and steel, and wide range of other engineering industries, the workers can run the risk of hearing damage. He reported that the OSHA rule i.e. the permissible noise exposure 90 dB for 8-hours workday with an exchange of 5dBA is being replaced and currently, permissible noise exposure limit of 85dBA with 3dBA exchange rate was adopted and expected that it may considerably reduce the noise-induced hearing loss of the industrial workers.

Vardhan et al. [94]studied on the assessment of heavy earth-moving machinery noise vis-à-vis routine maintenance in Indian mining industry. According to their report, exposure to noise from various types of equipment/machinery has been identified as a critical health hazard for personnel working in the Indian mining industry. Heavy Earth Moving Machinery (HEMM) used in mines have been identified as major sources of noise and several earlier investigators have proposed various types of retrofit measures on these machines to reduce noise. They evaluated the noise generation characteristics of HEMM as influenced by periodic maintenance. Detailed noise measurements were carried out in a large open pit coal mine located in India. The effect of maintenance on noise production was assessed for ten dumpers and three dozers by measuring the A-weighted one-third-octave band sound pressure levels after the machines had been subjected to maintenance at the end of 300 hours, 500 hours, 750 hours and 1000 hours of use. They have also taken measurements to assess the effect of maintaining specific HEMM systems noise characteristics at 1000 hours. As per their study, the assessment of sound pressure levels at each periodic maintenance revealed major sound level reductions with 1000 hours maintenance. Their experimental data also identified the major noise generating systems in HEMM as air systems, exhaust systems, cooling systems and fuel systems .

Pal et al. [95] studied the noise status in Kotah stone mines and discussed recent noise control methods applied to machineries that were used for production. They conducted noise measurement by using Modular Precision Sound Level Meter (B & K Type 2331) and Modular Precision Sound Analyzer (B & K Type 2260). According to their study, they found that the average noise levels of 99.2 to 100.6 dB (A) were observed during the cutting operation and from spectrum analysis, the results are discussed below:

1. All the activities except during idling operation of a Jhiri Machine produced high frequency (2 kHz to 4 kHz).

2. Idling operation produced mid frequency as well as high frequency (250Hz, 500Hz, and 1 kHz) dominant noise. It also showed a minimum deviation for considerable range of frequencies above 250 Hz.

They also pointed that noise control is required in Kotah stone mines and for this they recommended use of wet sacks on the rock floor to control noise. The sacks are to be placed near to the machine in such way that they do not hinder the smooth operation of the machine as well as do not affect the mobility of the personnel. However, sack laying area is to be determined after a thorough study of noise emission from rock interface by trial and error method.

Rylander [96] studied about noise, stress and annoyance and discussed about the effect of noise on human health. According to him, the energy related noise levels are poor predictions for the reactions in man as noise is always interpreted in the central nervous system, generating secondary and tertiary reactions that are not controlled by the brain cortex. The simulation of these reaction pathways in acute situations lead to involuntary reflexes and feelings of fright and despair. In chronic exposure situations a give-up stage may develop with reduced corporal and mental functions. in the acoustical panorama peak level noises usually cause the most pronounced effects as they stimulate reactions of fear and flight.

Pandey et al. [97] studied the environmental problems due to generation of noise from haul truck in mining industry. In their report, they mentioned the noise exposure limit for industrial workers as per CPCB (Central Pollution Control Board, New Delhi. The Central Pollution Control Board, India has recommended certain guidelines for the maximum permissible exposure to different intensities of sound with regard to occupational health and safety of the industrial workers. For a full shift of 8-hours work is permissible if the noise level is 90dB or less. For higher noise levels, there should be a 50% reduction in maximum permissible working time for every 3dB increase in noise level over a range of 90-114 dB, as shown in Table 2.31.

Table 2.31: Noise exposure limits for industrial workers (CPCB), 2000 [97]

| Exposure time (hours/day) | Limit in dBA |
|---|---|
| 8 | 90 |
| 4 | 93 |
| 2 | 96 |
| 1 | 99 |
| 1/2 | 102 |
| 1/4 | 105 |
| 1/8 | 108 |
| 1/16 | 111 |
| 1/32 or less | 114 |

Followings are some important conclusions of their research study:

- The haul truck operators are exposed to occupational noise level (TWA) ranging from 88.2 to 99.21 dBA during 8 hr daily work shift.
- 71% truck operators are exposed to occupational noise exceeding the maximum permissible level i.e. 90dBA.
- All (100%) truck operators are exposed to occupational noise exceeding the warning level i.e. 85dBA.
- On an average a truck operator is exposed to occupational noise level (TWA(8)) of 90.032 dBA during 8hr daily work shift.
- Daily noise dose received by the subjects ranges from 78 to 136 % with a mean of 105 %.
- Operator onboard time during work shift ranges from 386 to 435 minutes with a mean of 413 minutes.
- Average noise dose received by the subjects during off board time is 15%.
- The subjects are exposed to average noise level of 88 dBA during of haul truck, having the range of 80 to 90 dBA.

- Noise level during unloading of haul truck varies from 97 to 108 dBA with an average of 102.5 dBA.
- Average noise level during travel of loaded haul truck is 96 dBA where as, that of empty truck is 87.7 dBA.
- Average noise level during uphill travel of loaded haul truck is 103 dBA where as, that of empty truck is 95 dBA.
- It was found that average noise level during loaded travel uphill was maximum among all variables namely, during loading , unloading , load travel , empty travel, loaded travel uphill and travel uphill. average noise level can be arranged in descending order as follows :

Table 2.32: Average noise level of haul truck with different activity [97]

| Activity | Average noise level ($L_{avg}$) |
|---|---|
| Loaded travel uphill | 103.292 dBA |
| Unloading | 102.500 dBA |
| Loaded travel | 96.021 dBA |
| Empty travel uphill | 95.104 dBA |
| Loading | 88.396 dBA |
| Empty travel | 87.750 dBA |

Phillips et al. [98] studied the noise and vibration levels of rock drill in South-African gold mines. They have studied the noise and vibration levels of three hand-held rock drills (pneumatic, hydraulic and electric) those were currently used in South African mines, and a prototype acoustically shielded self-propelled rock drill. All four drills emitted noise exceeding 85 dB (A). The pneumatic drill reached levels of up to 114 dB (A), while the shielded self-propelled drill almost complied with the 85 dB(A) 8 h exposure limit. Vibration levels of up to 31 m/$s^2$ were recorded. These levels greatly exceed recommended and legislated levels. The following Tables (2.33 and 2.34 ) show the details of their study. Significant engineering advances will need to be made in the manufacture of rock drills to impact on noise induced hearing loss and hand arm vibration syndrome. Isolating the operator from the drill, as for the self-propelled drill, addresses the problems of both vibration and noise exposure, and is a possible direction for future development.

Spencer and Reeves [99] of National Institute for Occupational Safety and Health (NIOSH) conducted an investigation to quantify sound levels and to determine the amount of sound reduction provided by engineering noise controls installed in a talc processing plant. Baseline sound level and sound intensity measurements were performed at

Table 2.33: Drill penetration rates for the six configurations of rock drills [98]

| Configuration | Penetration rate (mm $min^{-1}$) |
|---|---|
| Self-propelled drill with standard drill steel | 300-400 |
| Self-propelled drill with cladded drill steel | 300 |
| Pneumatic drill: standard configuration | 350 |
| Pneumatic drill: muffled configuration | 395 |
| Hydraulic drill | 600 |
| Electric drill | 130 |

Table 2.34: Sound pressure levels at the three grid positions [98]

| Configuration | Behind operator [dB(A)] | Right of the operator [dB(A)] | Right further back [dB(A)] |
|---|---|---|---|
| Self-propelled drill with standard drill steel | 88.7 | 84.9 | 82.9 |
| Self-propelled drill with cladded drill steel | 84.1 | 86.1 | 84.1 |
| Pneumatic drill: standard configuration | 104.4 | 107.9 | 104.2 |
| Pneumatic drill: muffled configuration | 100.5 | 103.8 | 98.1 |
| Hydraulic drill | 98.9 | 103.4 | 98.1 |
| Electric drill | 92.4 | 94.7 | 94.6 |

the plant and the measurement locations were recorded for comparison to post-control measurements. Follow-up measurements were then made at the same locations after the initial noise controls were installed. Fig. 2.8 represents the installation of noise control at the talc processing plant.The plant subsequently decided to implement additional noise controls and the researchers returned to conduct measurements for a final analysis of all noise controls. They concluded that the most significant results showed a sound level reduction in the main mill area from a range of 93-104 dB(A) down to 90-94 dB(A).

Bealko [100] studied mining haul truck cab noise. Mining haul trucks comprise the majority of the equipment used in underground limestone mining operations and are known to emit high levels of noise. A previous study conducted by the National Institute for Occupational Safety and Health (NIOSH) indicates that 70-90 percent of all miners have a noise-induced hearing loss (NIHL) great enough to be classified as a hearing disability by retirement age. His experimental results demonstrate the public health need

(a) Curtains around FEM fans

(b) Curtains around Jeffery crusher

Figure 2.8: Noise controls at a Talc processing plant [99]

to protect the hearing of workers in the mining industry, including haul truck drivers .

Gorai and Pal [101] studied noise environmental quality in residential/commercial/ sensitive areas situated near the industrial (iron ore mining) complex. Their study is near one of the largest iron ore mine in India (Bailadila Iron Ore-Mining Complex). Bailadila Iron Ore Mine is situated at Kirandul village in the district of Dantewada (Chattisgarh). Accroding to their study, noise environmental qualities (NEQ) for each locality were determined from value function curves developed for each noise impact parameters identified. The study reveals that almost all the areas register noise stress situations as the observed resultant noise environmental quality [NEQ(R)] at all the locations exceeding the desirable noise environmental quality [NEQ(R)] of the corresponding locations. They getting concluded that the noise stress of almost all the residential areas (except Nehru colony) and sensitive areas are high as the evaluated NEQ(R) of the areas were less in comparison to the desirable limit of indicative permissible value.

Kivade et al. [102] studied the noise status of jackhammer drill machine in laboratory. As per their study, it is concluded that the penetration rate and sound level is increased by an increase in applied thrust up to an optimum point after which penetration rate and sound level decreases until the drill eventually stalls. Based on their study, they concluded that low applied trusts results in very low penetration rates and sound levels and excessive bounce of the drill resulting in an early bit wear. Increase in applied thrust improves the penetration rate and sound level up to an optimum thrust level due to better contact time between the bit and the rock and good transfer of energy from the drill to the rock.

## 2.9 Noise Impact Assessment

The six generic steps associated with noise environment impacts are (1) identification of levels of noise emissions and impact concerns related to the construction and operation of the development project (2) description of the environmental setting in terms of existing noise levels and noise sources, along with land use information and unique receptors in the projected areas. (3) procurement of relevant laws, regulations or criteria related to noise levels, land- use compatibility , and noise emission standards (4) conduction of impact prediction activities including the use of simple noise source specific models, comprehensive mathematical models, and/or qualitative prediction techniques based on the examination of case studies and the exercise of professional judgment (5) use of pertinent information from step 3, along with professional judgment and public input, to assess the significance of anticipated beneficial and detrimental impacts and (6) identification, development and incorporation of appropriate mitigation measures for the adverse impacts.These six steps are shown in Fig. 2.9:

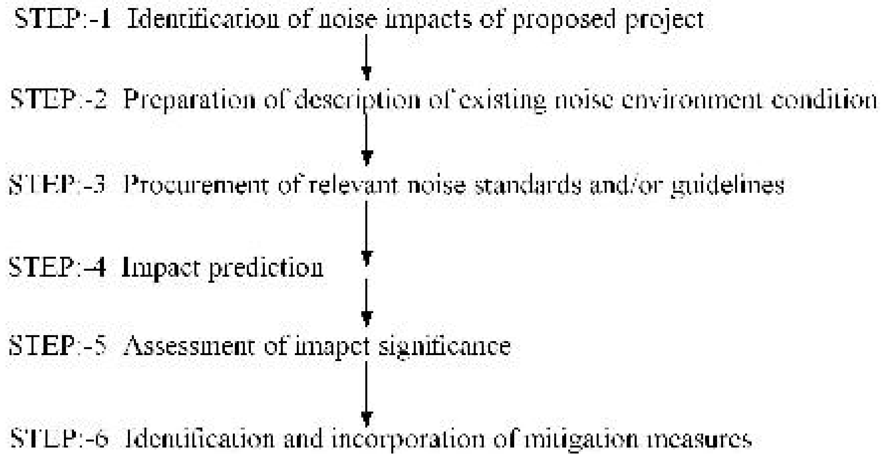



Figure 2.9: Conceptual approach for study focused on noise impact assessment. [79]

## 2.10 Noise Modelling and Prediction

Marsh [103] discussed the experience of the oil industry in specifying noise limits for new plants using the procedure published by the Oil Companies Materials Association. In his research study, he explained about the procedure of OCMA noise prediction model. The procedure defines a calculation method for predicting the noise in neighbouring areas due to a plant, which includes curves for deriving the excess attenuation due to ground effects. Long-term measurements, covering a period of one month to several years, have been made around four refineries and the median noise levels have been compared with predicted noise levels. In conclusion, he explained that the OCMA procedure is broadly correct.

Deeprose [104] predicted the noise level of some industrial pump and fan. They used the following formulae for predicting the sound pressure levels of fan as given below:

$$L_w = 27.5 + 8\log_{10} Q + 24\log_{10} P \tag{2.22}$$

$$L_w = 91 + 10\log_{10}(QP) + 30\log_{10} M/M_{20} \tag{2.23}$$

where $L_w$ = sound power level re $10^{-12}$ watts, Q = flow rate $m^3$/sec, P = pressure, M = match number and $M_{20}$ = match number at $20^0$ C.

Erskine [105] predicted the noise level of pumps and fans. They modified the predicted formula of fans as :

$$L_w = K_1 + 91 + 10\log_{10}(kW) + 30\log_{10} M/M_{20} \tag{2.24}$$

Where $L_w$ = sound power level in dB re $10^{-12}$ watts, kW = fan absorbed power, $K_1$ = octave band correction (Table 2.35), M = match no at gas temperature and $M_{20}$ = match no. at $20^0$C. The pump noise predicted formula is given below:

Table 2.35: Octave band correction [105]

| Octave band center frequency, Hz | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 |
|---|---|---|---|---|---|---|---|---|
| $K_1$ | -4 | -5 | -6 | -9 | -12 | -16 | -20 | -24 |

$$L_w = K_2 + 70 + 10\log kW \tag{2.25}$$

Where, $L_w$ = sound power level in dB re $10^{-12}$ watts, kW = pump shaft power and $K_1$ = octave band correction (Table 2.36).

Table 2.36: Octave band correction [105]

| Octave band center frequency, Hz | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 |
|---|---|---|---|---|---|---|---|---|---|
| $K_1$ | -6 | -6 | -6 | -8 | -98 | -10 | -15 | -20 | -20 |

Shield [106] developed a computer program which calculated the noise levels in factories. The collection of data for input to the program, formulae used in the calculation of noise levels and output from the program were described in his research article. The program was tested using data collected in a variety of workshops and factories. The results of two of these case studies were discussed, together with overall results for all cases considered, which showed that the program could predict sound levels with a high degree of accuracy. An interactive version of the program which enables a user to see immediately how certain changes to the data will affect noise levels was also described in the article. He used IBM 1130 machine and FORTRAN programming software for writing the program code of his computer based noise prediction model.

Marsh [107] discussed the new proposals for measuring the sound-power levels of industrial equipment. These are mentioned in the Noise Procedure Specification NWG-1, issued by the Oil Companies Materials Association, and are intended for use in the petroleum and petrochemical industries, but it is suggested that they could have wider applications in other industries. The shortcomings of the ISO engineering methods for determining sound-power level are discussed and compared with the proposed test methods. Basically in his study, he described about ISO 3744 (Determination of sound power levels of noise sources using sound pressure) and OCMA noise prediction model.

Manning [8] and his associates developed CONCAWE noise prediction model. The entire report was described on CONCAWE noise prediction model and the procedure how to apply the model in industry. In this report, calculation of all the attenuation factors was also discussed.

Marsh [108] discussed a propagation model (CONCAWE) for calculating neighborhood-noise from open-air industrial plants such as oil refineries and petrochemical plants. The model was developed from a preliminary model derived from a comprehensive survey of the literature on noise propagation. His research aim was to develop a model which used parameters and procedures available to engineers engaged in plant design. An experimental programme of measurements was carried out around three industrial plants over a period of about one year and this was used to modify the original model. The final model is based on six meteorological categories and contains separate attenuation values for spherical spreading, atmospheric absorption, ground effects, meteorological category, source/receiver height, and barrier effects. They were given as a function of frequency and distance, either as graphs or as polynomial equations for computer calculations. A statistical assessment was made to establish the confidence limits of the predictions in dB(A) and in octave bands from 63 Hz to 4 kHz. They were compared with the confidence limits of predictions by two other propagation models frequently used in Europe (OCMA and VDI) and were found to be significantly better. The CONCAWE noise prediction model was described in the following manner.

$$L_p = L_W + D - \sum_i K_i \tag{2.26}$$

where $L_p$ is the sound-pressure level at the receiving location (dB), $L_W$ is the sound power level of the source (dB), D is the directivity of the source toward the receiver (dB) and $K_i$ is an attenuation factor. The various attenuation parameters, $K_i$, can be attributed to a number of mechanisms and the following are considered to be the most important:

$K_1$ : loss due to spherical spreading (inverse-square law),

$K_2$ : loss due to atmospheric absorption,

$K_3$ : loss due to the presence of the ground,

$K_4$ : loss due to meteorological effects (wind, lapse rate),

$K_5$ : loss due to heights of source and receiver in relation to the topography,

$K_6$ : loss due to barriers and

$K_7$ : loss due to in-plant screening by other equipment.

International review of work area noise regulations on CONCAWE noise prediction model was declared in 1982. In this report, need of the CONCAWE noise prediction model was discussed. [109].

Now-a-days researchers use different software for the noise modeling which are summarized in Table 2.37. The most popular noise modeling software is ENM (Environmental Noise Model). It is developed by RTA Technology, released in DOS Version in 1986 and sold world wide. ENM simulates outdoor sound propagation and predicts noise levels from known attenuation due to noise source enclosures and other noise control measures.

Tonin [9] studied the environmental noise impact in petrochemical plants, mines and industrial complexes in Australia. He used various noise models such as OCMA, VDI, ENM, CONCAWE etc., for estimating the noise levels. He found that the above mentioned environmental noise models developed over the last decade were becoming more complex in their use of theoretical algorithms.

International Standard Organization (ISO) published the standard on atmospheric absorption of outdoor sound propagation in 1993 [10]. In that standard , the calculation of atmospheric absorption at each octave band was clearly described. The standard was named as ISO-9613-1(93). In 1996, ISO developed another standard on calculation of all the attenuations of outdoor propagation [11]. The empirical noise prediction model was expressed in the following equation

$$L_{fT}(DW) = L_W \ + \ D_c \ - A \tag{2.27}$$

where $L_W$ is the octave-band power level, in decibels, produced by the point source relative to a reference sound power of one picowatt (1 pW); $D_c$ is the directive correction. A is the octave-band attenuation, in decibels, that occurs during propagation from the point sound source to the receiver. The attenuation term A in equation 2.27 is given by equation 2.28;

$$A = A_{div} + A_{atm} + A_{gr} + A_{bar} + A_{misc} \tag{2.28}$$

where $A_{div}$ is the attenuation due to geometrical divergence. $A_{atm}$ is the attenuation due to atmosphere and it was calculated from ISO 9613-1 (1993) standard [10]. $A_{gr}$ is the attenuation due to ground effect. $A_{bar}$ is the attenuation due to barrier. $A_{misc}$ is the attenuation due to other miscellaneous effects.

Pal et al. [110] described the importance of noise prediction models in mining industry. They explained that, now-a-days numbers of noise prediction models are used in mining industry to predict the noise status before going for noise control. The three principal noise forecasting models used extensively in Europe are those of the Oil companies Materials Association (OCMA), the Oil Companies International Study Group for Conservation of Clean Air and Water Environment (CONCAWE) and the German Draft Standard VDI-2714 "Outdoor Sound Propagation", of which the first and the second relate to noise from petrochemical complexes, which can be used equally well to predict noise from mines and industrial complexes. The algorithms used in these models rely for greater part of on interpolation of experimental data which is a valid and useful technique, but their application are limited to sites which are more or less similar to those for which the experimental data was assimilated.

Australian state pollution control commission has developed a computerized noise propagation model, ENM, where real noise sources are substituted by an equivalent monopole point, line or plane source.

The basic features of these models are:

**i)** Determination of source power levels , $L_W$

**ii)** Computation of total atmospheric scenario by calculating the individual attenuation components $K_j$ as follows :

- Geometric spreading, $K_1$
- Source directivity, $K_2$
- Enclosure, $K_3$
- Building topography , $K_4$
- Air absorption , $K_5$

- Wind and temperature gradients, $K_6$
- Ground attenuation, $K_7$

**iii)** Computation of the resultant sound pressure level at an environmental point is done by equation 2.29.

$$L_p = \Sigma_{allsources}^{log}[L_w - (K_j)] \tag{2.29}$$

They also discussed the methods for development of the noise model and that are as follows

* All the noise sources are considered as point sources which radiate sound energy in all directions as if the sources in free field.

* The attenuation due to enclosure has been accounted while assessing sound power being emitted from the sources.

* The attenuation due to geometric spreading for spherical radiation has been considered to be in accordance with equation 2.30.

$$Attenuation(pointsource) = 10\log(4\pi R^2) \tag{2.30}$$

Where R is the distance from the source to receiver, (m).

* Attenuation due to meteorological effects

Pathak et al. [111] developed the Activity Accounting Technique (AAT) for predicting far field noise levels due to operation of specific set of mining machinery. The technique is based on the breaking down of the mining operations in to number of activities and establishing their duration and location. According to them, by estimating the noise levels due to those activities, the overall noise field near a surface mine can be predicted. Finally, they concluded that the Activity Accounting Technique has the scope of elaborate application for prediction of environmental noise near mining sites. In a system where the activities involved and their duration can be estimated, one can develop noise prediction model based on near field spectrum. However, this method will be much helpful if an acoustic database can be evolved for all the possible activities for different alternative equipment system. They expected that this technique can be used as a tool in surface mine design and planning for testing noise impacts of the alternative mining system.

Sean [113] developed a computer model for predicting noise spectrum of an engine cooling fan. In that model, he considered the effects of fan shroud radiator, condenser and engine compartment on the resulting narrow band and broad band sounds. His computer model obtained is validated experimentally with two completely different fan

Table 2.37: Different models of sound pressure level prediction [112]

| Sl. | Name of the Model | Basic equation |
|---|---|---|
| 1. | Oil Companies Materials Association (OCMA, UK, 1972) model | $L_p = \Sigma^{log}_{allsources}(L_w - K_1 - K_2)$ <br> $L_w$ is the sound power level, $K_1$is the attenuation due to spreading and soil type, $K_2$is the attenuation due to ground and meteorological effects. |
| 2. | VDI 2714/VDI (German Draft Standard, 1976) | $L_p = L_w + DI + K_0 - D_S - D_L - D_{BM} - D_D - D_G - D_e$ <br> $L_w$ is the ground power level , DI is the directivity index, $K_0$ is the solid angle reflection Index, $D_S$ is the air absorption factor, $D_{BM}$ is the ground and meteorological attenuation, $D_D$ is the attenuation due to vegetation, $D_G$ is the attenuation due to built-up areas, $D_e$is the attenuation due to barriers. |
| 3. | Oil Companies' International Study Group For Conservation of Clean Air and Water (CONCAWE, UK, 1981) model | $L_p = \Sigma^{log}_{allsources} L_w + D + K_1 - K_2 - K_3 - K_4 - K_5 - K_6 - K_7$ <br> $L_w$ is the sound power level, D is the directivity index of the source, $K_1$ is the attenuation due to clean air and water to geometric spreading. $K_2$ is the atmospheric absorption, $K_3$ is the attenuation due to ground effect, $K_4$ is the attenuation due to meteorological effects, $K_5$ is the correction for source height above ground, $K_6$ is the barrier shielding and $K_7$ is the in-plant screening. |
| 4. | BBN/EEI (Bolt Beranek and Newman Inc. Ltd./Edision Electric Institute.) | $L_p = L_w + D - 10\log(4\pi d^2) - [\frac{d}{100}(a_m) + \frac{d}{100}(a_a)] - [-3]$ <br> $L_w$is the sound power level, D is directivity index of source, d is the distance from the acoustic centre of a point source to receiver $a_m$ is the molecular absorption rate in dB per 100m, $a_a$ is the anomalous excess attenuation rate in dB per 100 m. |
| 5. | NORDFORSK Noise Model (by Lydteknisk Laboratorium, Denmark., 1982) | $L_p = L_w + \triangle L_\varphi \Sigma \triangle L$ <br> The Second term accounts for the directivity and the third terms accounts for various types of attenuation. |
| 6. | ENM (Environmental Noise Model by RTA Technology Pty. Ltd., Australia, 1985) | $L_p = \Sigma^{log}_{allsources} L_w + D - A_1 - A_2 - A_3 - A_4 - A_5$ <br> $L_W$is the sound power level; D is the directivity index of source. $A_1$is geometric spreading, $A_2$ is barrier attenuation, $A_3$is air absorption,$A_4$is wind and temperature effects and $A_5$is ground attenuation. |

assemblies. The calculated noise spectrum compared well with the measured data under the same working condition. The following Fig.2.10 shows the model description.

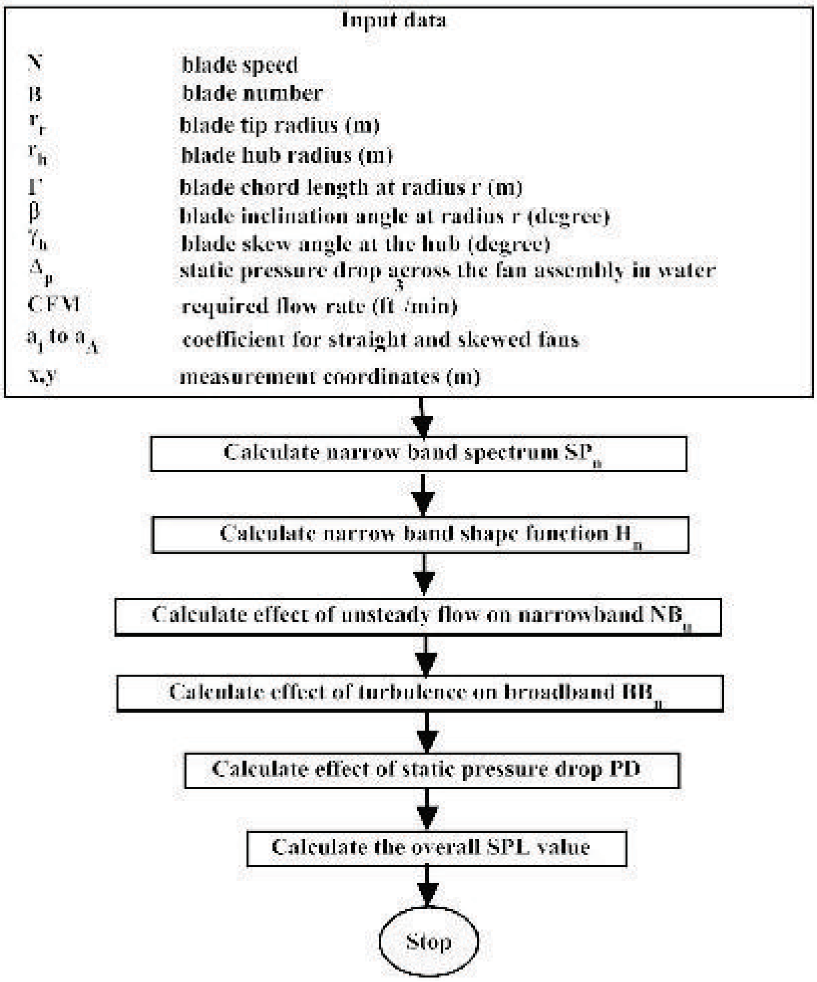



Figure 2.10: Flow chart for calculating noise spectrum of an engine cooling fan assembly [113]

Pathak et al. [114] developed an air attenuation model for noise prediction in surface mines and quarries. They have adopted the methodology developed by Sutherland et al. (1974) and developed model to predict attenuation due to absorption in air considering temperature and relative humidity. Table 2.38 shows the attenuation due to atmospheric absorption. The developed model is described in the following manner:

$$L_P = L_W - A_s - A_g - A_a - A_b + D_c - R_c \tag{2.31}$$

where $L_P$ =sound pressure level at the receiver's location; $L_W$ =sound power level of the equivalent acoustic centre of the work zones; $A_s$ = attenuation due to spreading; $A_g$ = attenuation due to ground absorption; $A_a$= attenuation due to air absorption; $A_b$ =

Table 2.38: Attenuation due to atmospheric absorption(after Sutherland et al. 1974) [18]

| Humidity % | Temperature ($^0C$) | $\alpha$ dB per 1000m | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 63Hz | 125Hz | 250Hz | 500Hz | 1000Hz | 2000Hz | 4000Hz | 8000Hz |
| 25 | 15 | 0.2 | 0.6 | 1.3 | 2.4 | 5.9 | 19.3 | 66.9 | 198.0 |
| | 20 | 0.2 | 0.6 | 1.5 | 2.6 | 5.4 | 15.5 | 53.7 | 180.5 |
| | 25 | 0.2 | 0.6 | 1.6 | 3.1 | 5.6 | 13.5 | 43.6 | 153.4 |
| | 30 | 0.1 | 0.5 | 1.7 | 3.7 | 6.5 | 13.0 | 37.0 | 128.2 |
| 50 | 15 | 0.1 | 0.4 | 1.2 | 2.4 | 4.3 | 10.3 | 33.2 | 118.4 |
| | 20 | 0.1 | 0.4 | 1.2 | 2.8 | 5.0 | 10.0 | 28.1 | 97.4 |
| | 25 | 0.1 | 0.3 | 1.2 | 3.2 | 6.2 | 10.8 | 25.6 | 82.2 |
| | 30 | 0.1 | 0.3 | 1.1 | 3.4 | 7.4 | 12.8 | 25.4 | 72.4 |
| 75 | 15 | 0.1 | 0.3 | 1.0 | 2.4 | 4.5 | 8.7 | 23.7 | 81.6 |
| | 20 | 0.1 | 0.3 | 0.9 | 2.7 | 5.5 | 9.6 | 22.0 | 69.1 |
| | 25 | 0.1 | 0.2 | 0.9 | 2.8 | 6.5 | 11.5 | 22.4 | 61.5 |
| | 30 | 0.1 | 0.2 | 0.8 | 2.7 | 7.4 | 14.2 | 24.0 | 58.4 |

attenuation due to pit slopes; $D_c$ = directivity corrections; $R_c$ = reflection correction.

They have also developed a computer module for use in determining the radii of curvature of ray paths in order to provide the statistical basis for deciding upon the base period of noise prediction in surface mines.

Mohalik and Pal [115] developed a noise model for mining complex with the help of ENM. According to them, the ENM model helps us to develop noise counter/profile of the mining complex. As such, it is possible to have an estimate of the noise levels of the exposed workers at different locations within the complex. In the case of new mines or reorganization/renovation of existing mine, this model helps in equipment/activity planning so as to have minimum noise exposure to the workers.

Rabeiy et al. [116] studied noise status of machineries in mining and industrial plants by using SL-130 and Bruel & Kajor type 1625 sound level meter. They also predicted noise in EI-Gedida mines and Assiut Cement Quarry by using VDI-2714 and ISO(1996) prediction algorithms. From their study, they found that in EI-Gedida mines, the sound pressure levels were greater than the acceptable level (90dBA) and also get similar result as in case of Assiut Cement Quarry. The noise status of different machineries used in EI-Gedida mines and Assiut Cement Quarry are mentioned in Tables(2.39-2.40).

Rabeiy et al. [117] studied noise status in Assuit Cement Plant (CEMEX). Their study was conducted in the limestone quarry and cement plant. Noise levels were predicted using the prediction model (ISO-9613-2-1996). Also, noise levels were calculated based on the machine data. Measurements were carried out using Bruel & Kjaer, sound level meter Type 2230 at different distances from the noise sources. Their study proved that

Table 2.39: Distance of measurements from each sources in EI-Gedida mine [116]

| Noise Sources | Sound Pressure Level (dBA) | Distance (m) |
|---|---|---|
| Power Shovel No. 216 | 102.4 | 4 |
| Power Shovel No. 215 | 113.7 | 4 |
| Power Shovel No. 209 | 105.63 | 4 |
| Power Shovel No. 203 | 107.1 | 4 |
| Power Shovel No. 211 | 104.35 | 4 |
| Power Shovel No. 271 | 99.4 | 4 |
| High power drill No. 504 | 100.82 | 1 |
| Low power drill No. 541 | 94.63 | 1 |
| Compressor | 102.8 | 1 |
| Low power drill | 89.63 | 1 |
| Compressor | 96.13 | 1 |
| Generator | 95.92 | 1 |
| Truck (caterpillar) | 98.42 | 2 |
| Bulldozer | 103.3 | 2 |

- The highest noise levels in Assiut Limestone Quarry is generated from Hydraulic Hammer (102.22 dBA) and crushing operations (100.1 dBA), are greater than the standard values; and the lowest noise levels are from the Belt drive (63.71 dBA) and the Belt conveyor (61.40 dBA)
- The worker's camp in Assiut Limestone Quarry is subjected to a noise level of (63.71 dBA) which is greater than the acceptable levels
- The management building in the quarry is subjected to a noise level of (69.17 dBA) which is higher than the acceptable limit.
- The safe distance from the quarry was found to be 1250 m.
- The management buildings in the plant are protected from high levels.
- The predicted noise levels can be used to evaluate the noise problem in the planning stage of new projects, in order to keep the working and ambient environment safe.

The sound pressure levels ($L_p$) at 1.5 m from the machines can be calculated based on horsepower and running time using the following equation:

$$L_p = 20 \log\,(HP) + K, dBA \tag{2.32}$$

where, $L_p$ = Maximum sound pressure level at a distance of 1.5 m from the machine. HP = Horsepower of the machine. K= Factor depends on type and the machine age and

Table 2.40: Sound pressure level of noise sources at Assiut Cement Quarry [116]

| Noise sources | Distance (m) | Octave band center frequency (Hz) | | | | | | | | dBA |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| Power shovel | 8 | 90.82 | 83.57 | 81.31 | 78.47 | 79.38 | 75.72 | 74.97 | 66.95 | 83.85 |
| Russian crusher | 3 | 88.28 | 89.68 | 86.07 | 88.43 | 87.28 | 84.67 | 78.83 | 71.97 | 91.58 |
| Breaking hummer | 4 | 68.24 | 90.89 | 87.28 | 88.57 | 87.28 | 81.61 | 88.75 | 84.61 | 93.71 |
| Loader | 8 | 83.64 | 85.00 | 82.30 | 83.11 | 77.68 | 74.67 | 71.14 | 67.28 | 83.95 |
| Belt conveyor | 4 | 64.49 | 67.32 | 63.52 | 59.89 | 58.50 | 52.20 | 50.59 | 41.62 | 61.40 |
| Belt drive | 4 | 73.23 | 79.29 | 75.16 | 70.50 | 67.08 | 60.72 | 58.47 | 56.20 | 63.71 |
| Compressor | 1 | 84.09 | 84.33 | 82.17 | 81.71 | 78.12 | 78.10 | 74.83 | 71.01 | 84.73 |
| Truck | 1 | 63.71 | 65.27 | 70.99 | 79.46 | 82.10 | 82.63 | 81.65 | 64.73 | 87.94 |
| Bulldozer | 1 | 90.28 | 92.15 | 85.33 | 89.90 | 87.96 | 83.94 | 81.87 | 72.19 | 92.25 |
| Drill | 1 | 76.70 | 77.98 | 84.94 | 88.58 | 91.52 | 94.96 | 93.67 | 88.92 | 99.69 |
| Roman crusher | 5 | 88.90 | 89.67 | 87.72 | 85.76 | 90.67 | 88.20 | 82.65 | 76.69 | 94.06 |

can be represented by the following relation.

$$K = K_0 + 0.00046(NHR), dBA \tag{2.33}$$

where, NHR=Machine running time in hours. $K_0$ = constant.

Harper and O'Brien [118] developed an empirical noise prediction model for the prediction of the composite sound pressure level and the equivalent noise exposure levels of groups of individuals from machines, used single and in combination in an underground environment based on the sound pressure level determined according to SABS-ISO 3744 under free field conditions. Basically their prediction model is used only for prediction of rock-drill noise. The methodology includes provision for the consideration of the effect of hearing protection devices and the use of multiple machines in combination and provides an indication of the potential costs of hearing compensation. Fig.2.11 shows the methodology of the designed model. The empirical noise prediction model predicted sound pressure level (SPL) at locations (i and j) and that can be calculated as follows:

$$L_{pi,j} = 10 \log \sum_{S=1}^{N_{Drills}} 10^{0.1 L_{ps0}\left(1 - 0.178\sqrt{x_s^2 + y_s^2}\right)} \tag{2.34}$$

where: $L_{pi,j}$ is the sound pressure level (dB or dBA) at location (i,j) $L_{ps0}$ is the sound pressure level of the $s^{th}$ source $x_s$ is the lateral displacement from the $s^{th}$ source $y_s$ is the horizontal displacement from the $s^{th}$ source NDrills is the total number of sources. They concluded that the current model was specific to stoping operations and would require further calibration for application to other underground environments such as

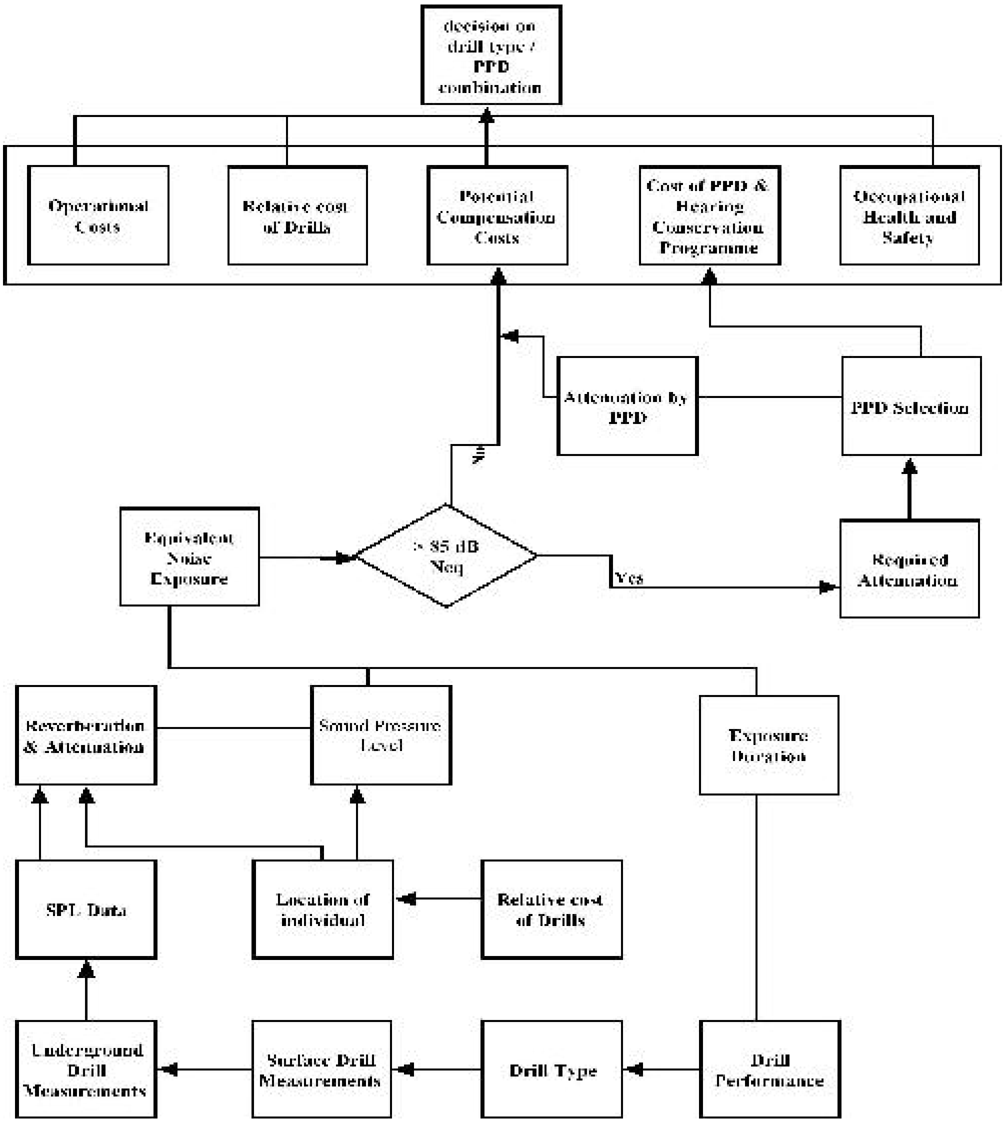



Figure 2.11: Flow chart of the model [118]

development ends and shaft sinking. While the model has been developed specifically for rock drills it could be used to evaluate the SPL of other stoping equipment such as pneumatic chain saws.

Sensogut and Cinar [119] developed an empirical model for noise propagation in opencast mines. In their case study, the data obtained from 312 measurement stations of sound propagation in panel 48 of the Tuncbilek open cast mine, Western Lignite Corporation, Turkey have been used to create an empirical model for such propagation. As well as the noise level recorded at these stations, atmospheric conditions were recorded also by the meteorological station located at the same panel. A total of 95,000 noise values were recorded at these stations. In addition the distances of the measurement stations to the effective source of noise and to the working slope, the meteorological effects and the number of noise sources were defined for each of 312 measurement stations. Using these data, the proposed model was tested against the noise measurements. Tables (2.41 and 2.42) shows the details of their study . Their empirical model for the A-weighted noise levels were follows:

$$L_t = L_{eq} - L_m + L_y + L_a + L_n \tag{2.35}$$

where $L_t$ represents the estimated noise level. The parameter $L_y$ is included only when the distance between the source of noise and the working surface is around 30 m as the effect of reflected waves was not determined beyond this distance. The parameter $L_n$ is included only when the distance between two sources of noise is less than 10 m.

Table 2.41: The equivalent noise levels at the haul road [119]

| Haul roads | Number of measurements | $L_{eq}$ (dB) |
|---|---|---|
| $1^{st}$ haul road | 394 | 71.2 |
| $2^{nd}$ haul road | 376 | 69.4 |
| Shared roads | 418 | 72.3 |

Table 2.42: A-weighted noise levels to which truck drivers are exposed [119]

| Position | Average time (s) | Window closed (dB) | Window open (dB) |
|---|---|---|---|
| Pre-waiting | 51 | 66.0 | 85.5 |
| Manoeuvre beside the shovel | 48 | 72.3 | 89.7 |
| Waiting beside the shovel | 111 | 70.3 | 82.8 |
| Loading instant | 138 | 72.5 | 86.1 |
| Haulage when loaded | 82 | 77.1 | 95.7 |
| Manoeuvre at the spoil area | 36 | 74.0 | 90.8 |
| Dumping | 30 | 76.0 | 94.2 |
| Haulage when empty | 98 | 77.8 | 94.7 |
| The equivalent noise level for one cycle ($L_eq$) | | 73.3 | 89.2 |

## 2.11 Application of Soft-Computing Techniques in Noise Prediction

Soft computing techniques viz. ANN (Artificial Neural Network), FUZZY logic, Genetic Algorithm etc are widely used for prediction of the air quality, soil and water quality in environmental science and engineering. However, there have been limited use of these techniques in noise prediction so far.

Cammarata et al. [120] proposed a neural approach to filter the data provided by acoustic measurement. The model was based on the use of a Kohonen Self-Organizing Map network which, in the learning phase recevies correct acoustic measurements.Their study present a strategy based on neural networks for the automatic recognition of acoustic measurements affected by errors. In their proposed model, Back Propagation network is used to extract the functional relationship between particular road parameters (number of vehicles, average height of buildings, road width) and the level of sound pressure. They concluded that, the proposed model confirms correct extraction of the functional relationship by the BPN model.

Fortuna et al. [121] developed a Neuro-Fuzzy model for prediction of urban traffic noise. In their paper, they described a Neuro-Fuzzy approach to obtain the relationships between the parameters involved in the characterization of noise pollution in urban traffic . A Fuzzy Neural Network which implements a fuzzy reasoning with constant consequences has been chosen. They concluded that their developed model could overcome some difficulties which appear both in neural and fuzzy modelling and gives a satisfactory performances with a reasonable computational cost .

Cammarata et al. [122] proposed neural network architecture for noise prediction in traffic place. They used BPN (Back propagation network) and LVQ (learning vector quantization network) for predicting noise and they found that it gave better prediction than the older statistical model. They used BPN for predicting the noise by use of an LVQ network as a filter of wrong measurements.

Caponetto et al. [123] developed a adaptive fuzzy model for noise prediction based on Genetic algorithm (GA). In their proposed model, Takagi-Sugeno approach was adopted applying a genetic algorithm during the optimization phase. They took the genetic algorithm parameters such as crossover probability (0.06), mutation probability (0.003), population size (30), number of generation (20) and chromosome length (14 bits per parameter). From their study, they concluded that , the GA based fuzzy model gave result with less computational value .

Verkeyn et al. [124] developed a fuzzy model for predicting noise annoyance. They presented a fuzzy rule based model for the prediction of traffic noise annoyance. Several inference schemes were compared for their performance in prediction capabilities as well as in speed. They concluded that the designed model showed that the fastest implementation does an equally good job, after optimization of certainty degrees attached to the rules. For this optimization, a genetic algorithm is applied in their model.

Stoeckle et al. [125] used neural networks for classification of urban environmental sound sources. The overall aim of their research was to provide new strategies for acoustic monitoring of complex urban environments. The specific aim of their research was to determine features of sound from commonly existing sources to enable automated source recognition. Their paper reported the use of Fast Fourier Transforms in order to produce spectral data of sounds from different sources for the classification using neural networks.

Botteldooren et al. [126] used fuzzy rule based engine to predict noise annoyance. They predicted noise annoyance that was reported by individuals in a social survey. They explained in their article, that the rules proposed by the human expert and are based in linguistic variables. The approach then adapts the sufficiency degree or certainty of a rule to tune the model to a particular survey. Although all possible relations between exposure, attitudinal, emotional, personal, environmental and social variables were not included in the model as yet, the benefits of the new approach were clearly demonstrated. They also reported that the major limitation that remains was the varying theoretical and empirical basis of the expert for different subset of annoyance determinants.

Zaheeruddin et al. [127] developed a neuro-fuzzy model for predicting the effects of noise pollution on human work efficiency as a function of noise level, type of task, and exposure time. Their model results revealed that the work efficiency depends to a large extent on the nature of task in addition to exposure time and noise level.

Zaheeruddin and Jain [128] developed a fuzzy model for noise induced hearing loss. In that model they took three inputs as noise level, duration of exposure (years), frequency and one output as hearing loss. They used fuzzy logic to interpreted the inputs and outputs with IF-THEN rules and Mamdani approach. Their model was developed on the basis of field surveys of WHO & EPA. The model was based on the assumption that the hearing loss is a function of noise level, duration of exposure and frequency. The hearing loss is not appreciable below 1 kHz and becomes pronounced between 3-5 kHz for 80-95dBA noise level.

Zaheeruddin and Jain [129] developed a fuzzy model for determining the work efficiency of humans as a function of noise level, exposure time, and the type of task. Their modelling technique was based on the concept of fuzzy logic, which offers a convenient way of representing the relationships between the inputs and outputs of a system in the form of IF-THEN rules. The model was established on the basis of surveys that the impact of noise on work efficiency depends to a large extent on the type of tasks. They explained in their article that the complex tasks got significantly affected even at much lower noise levels whereas the simple tasks remain unaffected up to very high noise levels. In their model, they have taken the duration of noise exposure as an important factor in determining the work efficiency. Finally, they have compared their model results with the deduction based on the criterion of Safe Exposure Limit recommended for industrial workers.

Zaheerudin et al. [130] gave a fuzzy model for predicting noise induced annoyance. The fuzzy model approach offers a convenient way of representing the relationships between the inputs and outputs of their system in the form of simple IF-THEN rules. Annoyance in this model is considered as a function of noise level, its duration of occurrence and the socio-economic status of a person. The proposed model was implemented on the fuzzy logic toolbox of MATLAB, using both Mamdani and Sugeno techniques.

Zaheeruddin and Garima [131] developed a neuro-fuzzy model for predicting the effects of noise pollution on human work efficiency as a function of noise level, type of task, and exposure time. Their model was based on Fuzzy logic toolbox of MATLAB© using ANFIS.

Zaheerudin and Jain [132] proposed fuzzy expert system to find noise-induced sleep disturbance.They have represented the relationships between inputs and outputs of the proposed system in the form of IF-THEN rules. Noise induced sleep disturbance is considered as annoyance is generally considered as a function of noise level, its duration of occurrence and the socio-economic status of a person and it contains high vagueness.Hence their proposed fuzzy model easily approximated the system.

Parbat and Nagarnaik [133] developed an artificial neural network model for predicting the road traffic noise. Their paper illustrated the study on feasibility of ANN modeling for road traffic noise prediction at Yavatmal city, district place of Vidarbha region in Maharashtra state. Sixteen locations were identified at uninterrupted and interrupted traffic flow conditions for conducting field studies Traffic volume study (composition & classified traffic volume) and noise level study were carried out simultaneously. They used Artificial Neural Network software (Elite ANN) for traffic noise prediction. In their model, the network used feed forward back propagation algorithm.

Zaheerudin and Jain [134] developed an expert system using fuzzy approach to investigate the effects of noise pollution on speech interference. The speech interference measured in terms of speech intelligibility was considered to be a function of noise level, distance between speaker and listener, and the age of the listener. The main source of model development is the reports of World Health Organization (WHO) and field surveys conducted by various researchers. They developed their models by using Fuzzy Logic Toolbox of MATLAB using both Mamdani and Sugeno techniques. The results were found to be in good agreement with the findings of World Health Organization (WHO) and U.S. Environmental Protection Agency (EPA). The study reveals that for good communication at normal distances ('short' and 'medium') encountered in ambient environment, the noise level should not exceed 65 dB(A) for 'young' and 'middle aged', and 55 dB(A) for 'old' persons. Their developed models established the usefulness of the fuzzy technique in studying the environmental problems where the cause-effect relationships are inherently fuzzy in nature.

Golmohammadi et al. [135] developed fuzzy logic based model for assessment of noise exposure risk in an industrial workplace (Glass Factory) in Hamadan, west of Iran. Their work proposes an exposure assessment method of occupational noise based on Fuzzy sets. The noise assessment by Fuzzy logic method involves the primary investigation of the workplace, determined inputs and output variables, Fuzzification, Fuzzy rules, Fuzzy inference method and Defuzzification. Their devloped fuzzy method assist to obtain a clear and integrated approach to risk assessment of noise exposure.

Torija et al. [136] used back-propagation neural networks to predict the short-term (5-min as integration period) sound pressure level and both temporal structure and spectral composition of the sound-pressure level of urban environments. The proposed ANN affords noteworthy precision in predicting the descriptors used here, proving much more effective than the use of Multi Linear Regression (MLR).

Kumar et al. [137] studied 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. As per their study, to overcome these above said problems, researchers and acoustical engineers have applied the artificial neural network in the field of traffic noise prediction. They concluded that ANN based models were capable of predicting traffic noise more accurately and effectively as compared to deterministic and statistical models.

## 2.12 Conclusion

Noise is a dangerous form of environmental pollution. Increased mechanization of opencast and underground mines to augment high production and productivity, has accentuated the noise problem to alarming levels. Prolonged exposure of miners to high doses of noise causes NIHL temporarily /permanently and several other health hazards. Of late, in view of its associated adverse physiological impacts, it has received significant public attention and necessitated the government to promulgate, The Noise Rules,2000 and 2010.

Systematic monitoring of various noise sources as well as exposure risk of miners should be taken up before formulating appropriate control measures to minimize noise induced risks. Since 1990s, a number of studies have been carried out on noise pollution in Indian mines to assess noise level generated by equipments used in opencast and underground mines and beneficiation plants, 1/1 and 1/3 octave band analysis and hearing acuity of miners. There has been limited documentation in mining companies on hearing loss of miners. In India, as per DGMS guidelines (Circular No. 18 of 1975 and No.5 of 1990), it is mandatory for every mine to conduct noise level survey, engineering and administrative controls of noise at workplace, audiometric examinations of workers and conducting hearing conservation programme. It is also observed that noise levels in majority of the mining operations are higher than the recommended limit of 90 dB

(A). Hence the present research work highlights the importance of prediction of opencast mining machineries noise.Most of the models are environmental and takes into account the meteorological effects and other attenuation factors which help in estimating accurate sound power level from the field measurements.

A number of software is available in the market to predict noise in mines. Particularly in mining industry, some statistical models were used, however, due to complexity of these models and due to the non-user friendly environment, very less applications were found. Therefore, Soft-Computing applications may play a major role to overcome these difficulties. In comparison to mathematical models, soft-computing based models were successfully implemented in prediction of traffic noise, prediction of noise annoyance and noise-induced hearing loss, where no such applications of soft-computing models in opencast mining machineries noise prediction were found. It is expected that in future, soft computing techniques will be increasingly used for noise modeling.

# CHAPTER 3

# NOISE PREDICTION IN MINING INDUSTRY USING MATHEMATICAL MODELS

## 3.1 Introduction

With increasing mechanization of mining operations and the use of heavy earthmoving machineries in opencast mines, the noise level have increased over the years. To maintain the good working environment in mines, appropriate noise survey of machineries should be conducted. The measured sound pressure level (SPL) for the equipments by sound measuring devices are considered inaccurate due to instrumental error, attenuation due to geometrical aberration, atmospheric absorption etc. In this chapter, different noise prediction models (frequency and non-frequency)have been discussed and contour map of noise sources in a bauxite mine is illustrated.Noise measurements, carried out in the field are prone to various measurement errors e.g. Instrumental error, meteorological effect and other attenuation factors. These corrective factors must be applied to the measured noise to get the accurate value. Most of the noise prediction models use the empirical equations to compute sound power level from measured sound pressure level. Based on the computed measurements suitable noise control measures can be adopted. Details of the studies have been discussed in Chapter 3 (subsection 3.2.1 to 3.2.4).

## 3.2 Outdoor Noise Prediction

The sound pressure level (SPL, $L_p$) at an observation point may be defined as the sum of sound power level ($L_w$) of the source; a geometric spreading factor, K, which is dependent upon the type of source and accounts for geometrical spreading as the sound propagates away from the source; a directivity index, $DI_M$, which accounts for directional properties of the source, including influences of reflections other than those in the ground plane; and an excess attenuation factor, $A_E$.The excess attenuation factor in turn is the sum of terms including ground reflection, atmospheric effects, etc. The general noise prediction model is written as the following [18, 25]:

$$L_p = L_w - K + DI_M - A_E \tag{3.1}$$

For N sources, the sound pressure level may be computed as the sum of contribution as in the following equation:

$$L_p = 10\log_{10}\sum_{i=1}^{N} 10^{L_{pi}/10} \tag{3.2}$$

Where $L_{pi}$ is the sound pressure level due to the $i^{th}$ source.There are many noise prediction models available in the literature. These prediction models are basically of two types, octave band frequency independent and octave band frequency dependent. The following sections represent octave band frequency independent model (Verein Deutscher Ingenieur(VDI)-2714) and octave band frequency dependent models viz. CONCAWE (Conservation of Clean Air and Water in Europe), ISO(International Standard Organization)-9613-2, ENM (Environmental Noise Model) etc.Octave band independent model (VDI-2714) is generally based on the average octave band results. All the calculations of attenuation factors are determined in dB (A) only. In frequency independent model, it assumes that all the results have equal impact at all frequencies. To study the actual effect of SPL in all frequency bands, to study the individual characteristics of attenuation factors in all frequency bands, frequency dependent noise prediction models were required.

### 3.2.1 VDI-2714 Noise Prediction Model

In 1976, the VDI (Verein Deutscher Ingenieur) draft code 2714 on Outdoor Sound Propagation was issued by the VDI Committee on Noise Reduction [9]. The sound pressure level at an environmental point is calculated from the following equation :

$$L_p dB(A) = \Sigma_{allsources}^{log}[L_W + K_1 - 10\log(4\Pi R^2) + 3dB - K_2 - K_3 - K_4 - K_5 - K_6 - K_7] \tag{3.3}$$

where,

$L_w$ = source power level re $10^{-12}$ watts

$K_1$ = source directivity index

$-10log(4\Pi R^2)+3dB$ = geometric spreading term including infinite plane coinciding with the source

R = source to receiver distance

$K_2$ = atmospheric attenuation = $10\log(1 + 0.0015R)dB(A)$
$K_3$ = attenuation due to meteorological conditions
= $[(12.5/R^2) + 0.2]^{-1}$ dB(A)
$K_4$ = ground effects = $10\log[3 + (R/160)] - K_2 - K_3dB(A)$
$K_5$ = barrier value (0-10) = $10log(3 + 20d)$ dB(A)
d = barrier path difference
$K_6$ = attenuation due to woodland areas
$K_7$ = attenuation due to built-up areas.The above calculations are performed in units of dB(A) only, not in octaves for the OCMA (Oil Companies Materials Association) and other models such as (VDI-2720, ISO-9613-2, CONCAWE etc.) [9].VDI-2714 model is a frequency independent model. Using the equation (3.3), results can be calculated easily. This is very simple and widely used model. As this model output was used to develop soft computing based prediction models, the details of VDI-2714 were presented in Chapter 5.

### 3.2.2 CONCAWE NOISE PREDICTION MODEL

In 1977, CONCAWE (Conservation of Clean Air and Water in Europe) contracted Acoustic Technology Ltd of Southampton to review the available literature to date on sound propagation in the atmosphere and to update the algorithms used in the petroleum consortium's OCMA (Oil Companies Material Association) scheme, 1972. The sound pressure level received at a point remote from the noise source is a function of the acoustic power of the source and the various mechanism of attenuation. It is possible to separate the dominant factors affecting the attenuation of sound and examine the contribution of each individually. The major attenuation mechanism could be defined as [8, 18, 25, 107–109]:

- geometrical spreading
- atmospheric absorption
- ground effects
- meteorological effects
- barriers
- in-plant screening.

Thus, in a simplified form the sound pressure level at a remote point can be related to the source sound power level by the expression:

$$L_P = L_W + D - \sum K(dB) \tag{3.4}$$

where $L_P$ is the sound-pressure level (dB re 20 $\mu$Pa), $L_W$ is the sound-power level (dB re $10^{-12}$W), D is the directivity index of the source in dB and $\sum$K is the sum of the losses defined above.

The CONCAWE scheme requires octave band analysis. Meteorological corrections in this scheme are based on analysis of Parkin and Scholes' data together with measurements made at several industrial sites. The excess attenuation in each octave band for each category tends to approach asymptotic limits with increasing distance.

#### 3.2.2.1 Geometrical Spreading ($K_1$)

$$K_1 = 10 \log 4\pi d.^2 \tag{3.5}$$

where d is the source-receiver distance. the formula implies spherical propagation away from the source. Any reflecting areas, including the ground surface, are taken into account in the factors $K_3 - K_7$.

#### 3.2.2.2 Atmospheric Absorption($K_2$)

Values of the atmosphere attenuation may be obtained from tables in CONCAWE document for the relevant values of temperature and relative humidity. For octave band width considerations the values corresponding to the lower 1/3rd octave band centre frequency should be chosen. For pure tone considerations values of the atmospheric absorption at the particular frequency should be used, making linear interpolation between tabulated values where necessary. Table 3.1 represents the atmospheric absorption values at different frequencies at $30^0$C.

Table 3.1: Atmospheric Absorption Values, dB km$^{-1}$, at $30^0$C

| *Frequency (Hz)* | *Relative Humidity, %* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 55 | 60 | 65 | 70 | 75 | 80 | 85 | 90 | 95 | 100 |
| 63 | 0.1 | 0.1 | 0.1 | 0.1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 125 | 0.3 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.1 |
| 250 | 1 | 0.9 | 0.9 | 0.8 | 0.8 | 0.7 | 0.7 | 0.6 | 0.6 | 0.6 |
| 500 | 3.2 | 3.1 | 2.9 | 2.9 | 2.7 | 2.6 | 2.5 | 2.4 | 2.3 | 2.2 |
| 1000 | 7.4 | 7.5 | 7.5 | 7.4 | 7.3 | 7.2 | 7.1 | 7.0 | 6.9 | 6.8 |
| 2000 | 12.9 | 13.2 | 13.5 | 13.8 | 14.1 | 14.3 | 14.5 | 14.7 | 14.8 | 14.9 |
| 4000 | 24.7 | 24.5 | 24.4 | 24.5 | 24.6 | 24.8 | 25.1 | 25.4 | 25.7 | 26.0 |
| 8000 | 67.5 | 64.2 | 61.6 | 59.5 | 57.9 | 56.6 | 55.5 | 54.7 | 54.1 | 53.6 |

#### 3.2.2.3 Ground Attenuation($K_3$)

For acoustically 'hard' surfaces, such as concrete or water: $K_3$=-3 dB for all frequencies and distances. For all other surfaces $K_3$ may be determined as a function of frequency and distance from the graphs given in Figure 3.1. Where the propagation is partially over an acoustically 'hard'surface and partially over a surface of finite acoustic impendence, values for $K_3$ may be obtained by using only the distance traversed across the 'soft' ground and obtaining the appropriate value from Figure 3.1. Table 3.2 represents the equations for ground effects at different frequencies.

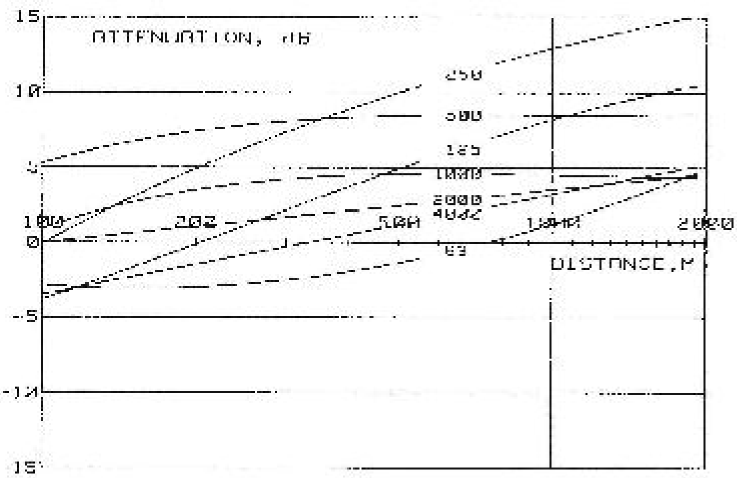



Figure 3.1: Ground Attenuation curve

Table 3.2: Equations for ground effects at different frequencies

| Frequency (Hz) | Equation for Ground effects |
|---|---|
| 63 | 33.4 - 35.04 (log d) + 9.159 $(\log d)^2$ - 0.3508 $(\log d)^3$ |
| 125 | 8.96 - 35.8 (log d) + 20.4 $(\log d)^2$ - 2.85 $(\log d)^3$ |
| 250 | -64.2 + 48.6 (log d) - 9.53 $(\log d)^2$ + 0.634 $(\log d)^3$ |
| 500 | -74.9 + 82.23 (log d) - 26.921 $(\log d)^2$ + 2.9258 $(\log d)^3$ |
| 1000 | -100.1 + 104.68 (log d) - 34.693 $(\log d)^2$ + 3.8068 $(\log d)^3$ |
| 2000 | -7.0 + 3.5 (log d) |
| 4000 | -16.9 + 6.7 (log d) |

#### 3.2.2.4 Meteorological Correction ($K_4$)

The attenuation due to meteorological factors are function of frequency, distance and meteorological category as defined in Tables 3.3 and 3.4. For meteorological category 4 the correction is zero in all cases. The correction due to refractions by wind and temperature gradients is given in Table 3.5.

#### 3.2.2.5 Source and / or receiver Height Correction ($K_5$)

The decrease in excess attenuation due to source height, where this is greater than 2 meter may be obtained from the following relationship:

Table 3.3: Pasquill (meteorological) stability categories

| *Wind Speed m/s* * | *Day time Incoming Solar Radiation mW/Cm²* | | | | *1 hour before Sunset or after Sunrise* | *Night-time Cloud Cover (octas)* | | |
|---|---|---|---|---|---|---|---|---|
| | > 60 | 30-60 | < 30 | Overcast | | 0-3 | 4-7 | 8 |
| ≤ 1.5 | A | A-B | B | C | D | F or G ** | F | D |
| 2.0 - 2.5 | A-B | B | C | C | D | F | E | D |
| 3.0 - 4.5 | B | B-C | C | C | D | E | D | D |
| 5.0 - 6 | C | C-D | D | D | D | D | D | D |
| > 6 | D | D | D | D | D | D | D | D |

* Wind speed is measured to the nearest 0.5 m/s

** Category G is restricted to night-time with less than 1 octa of cloud and wind speed of less than 0.5 m/s

Table 3.4: Pasquill (meteorological) stability categories

| *Meteorological category* | *Pasquill stability category and wind speed (m/s) (positive is towards receiver)* | | |
|---|---|---|---|
| | A,B | C,D,E | F,G |
| 1 | v <- 3.0 | – | – |
| 2 | -3.0 <v<- 0.5 | v <- 3.0 | – |
| 3 | -0.5 <v<+ 0.5 | -3.0 <v<- 0.5 | v <- 3.0 |
| 4* | +0.5 <v<+3.0 | -0.5 <v<+ 0.5 | -3.0 <v<-0.5 |
| 5 | v >+3.0 | +0.5<v<+3.0 | -0.5 <v<+ 0.5 |
| 6 | – | v >+3.0 | +0.5<v<+3.0 |

* Category with assumed zero meteorological influences

For $(K_3 + K_4) >$ - 3 dB

$K_5$= $(K_3 + K_4 + 3)$ ( $\gamma$ - 1) dB

$\gamma$ is obtained from the graph as a function of grazing angle $\psi$, where

$$\psi = \tan^{-1}[\frac{h_s + h_r}{d}] \tag{3.6}$$

and $h_s$ and $h_r$ are the source and receiver heights respectively. when $(K_3 + K_4) <$ - 3 dB, $K_5 = 0$

The model had been validated for a receiver height of 1.2 m. Sound levels for greater elevations may be calculated using the above formula.

#### 3.2.2.6 Barrier Shielding($K_6$)

The attenuation due to barriers is calculated using the method of Maekawa but modified to account for wind and temperature gradients using the approach of De Jong and Stusnick. The presence of a discrete barrier may reduce ground effects and it is proposed that this be covered by recalculating $K_5$ based on the barrier height and barrier-receiver

Table 3.5: Equations for meteorological effects at different frequencies for different categories [8]

| Frequency (Hz) | Equations for Meteorological Effects | | | | |
|---|---|---|---|---|---|
| | Category 1 | Category 2 | Category 3 | Category 5 | Category 6 |
| 63 | - 38.9 - 26.4 (log d) -2.84 $(\log d)^2$ - 0.234 $(\log d)^3$ | 16.1 - 28.43 (log d) + 14.4 $(\log d)^2$ - 2.1 $(\log d)^3$ | - 4 + 2 (log d) | 3.35 - 2.26 (log d) + 0.407 $(\log d)^2$ - 0.0572 $(\log d)^3$ | 69.3 - 73.2 (log d) + 24.688 $(\log d)^2$ - 2.7531$(\log d)^3$ |
| 125 | - 137 + 142(log d) -46.8 $(\log d)^2$ + 5.14 $(\log d)^3$ | - 23.2 + 19.53 (log d) - 4.646 $(\log d)^2$ + 0.3358 $(\log d)^3$ | - 3 + 1.5 (log d) | 6.8 - 3.4 (log d) | 29.53 - 25.62 (log d) + 6.286 $(\log d)^2$ - 0.4904$(\log d)^3$ |
| 205 | - 104 + 100(log d) -30.3 $(\log d)^2$ + 3.03 $(\log d)^3$ | - 84.8 + 91.93 (log d) - 30.873 $(\log d)^2$ + 3.4295 $(\log d)^3$ | - 100.6 + 101.23 (log d)- 32.352 $(\log d)^2$ + 3.4306 $(\log d)^3$ | 7.4 - 4.2 (log d) | 31.7 - 23.81 (log d) + 4.055 $(\log d)^2$ - 0.1043$(\log d)^3$ |
| 500 | - 20.9 + 3.86(log d) + 6.39 $(\log d)^2$ - 1.43 $(\log d)^3$ | - 133.7 + 142.63 (log d) - 47.851 $(\log d)^2$ + 5.3118 $(\log d)^3$ | - 96.8 + 102.98 (log d)- 34.868 $(\log d)^2$ + 3.9016 $(\log d)^3$ | 7.4 - 4.2 (log d) | 19.8 - 8.8 (log d) - 2.035 $(\log d)^2$ + 0.6747$(\log d)^3$ |
| 1000 | - 54.3 + 39(log d) - 4.92 $(\log d)^2$ - 0.239 $(\log d)^3$ | - 148.2 + 164.99 (log d) - 56.287 $(\log d)^2$ + 6.3422 $(\log d)^3$ | - 150 + 160.95 (log d)- 54.786 $(\log d)^2$ + 6.1604 $(\log d)^3$ | 104.6 - 108.03 (log d) + 35.2955 $(\log d)^2$ - 3.8227$(\log d)^3$ | 123.4 - 127.6 (log d) + 42.017 $(\log d)^2$ -4.584$(\log d)^3$ |
| 2000 | - 69.9 + 63.6(log d) - 16.9 $(\log d)^2$ + 1.43 $(\log d)^3$ | - 143.0 + 142.18 (log d) - 44.5097 $(\log d)^2$ + 4.6195 $(\log d)^3$ | - 116.3 + 120.85 (log d)- 39.944 $(\log d)^2$ + 4.378 $(\log d)^3$ | 60.3 - 64.07 (log d) + 21.458 $(\log d)^2$ -2.3784$(\log d)^3$ | 82.3 - 90.98 (log d) + 31.444 $(\log d)^2$ -3.584$(\log d)^3$ |
| 4000 | - 126 + 128(log d) - 40.4 $(\log d)^2$ + 4.24 $(\log d)^3$ | - 125.4 + 124.74 (log d) - 38.807 $(\log d)^2$ + 4.017 $(\log d)^3$ | - 127.5 + 135.12 (log d)- 45.709 $(\log d)^2$ + 5.1113 $(\log d)^3$ | 28.7 - 20.1 (log d) + 2.688 $(\log d)^2$ + 0.0957$(\log d)^3$ | 66.4 - 60.77 (log d) + 16.409 $(\log d)^2$ -1.4457$(\log d)^3$ |

distance. The barrier attenuation is based on the calculation of a Fresnel number, N derived from diffraction theory and given by

$$N \ = \pm \ \frac{path \ \ length \ \ difference}{\frac{\lambda}{2}} \tag{3.7}$$

where N is the familiar Fresnel number, and $\lambda$ is the wavelength.

$$\begin{array}{rll} -0.3 & \leq N < -0.02 & K_6 = 5.65 + 66N + 244N^2 + 287N^3 \\ -0.02 & \leq N < 1.0 & K_6 = 5.02 + 21.1N + 19.9N^2 + 6.69N^3 \\ 1.0 & \leq N < 18.0 & K_6 = 10 \log N + 13 \\ & N \geq 18.0 & K_6 = 25 \end{array} \tag{3.8}$$

#### 3.2.2.7 In-Plant Shielding($K_7$)

It can be concluded that, in CONCAWE model, shielding of sources by typical plant found in refineries is negligible and hence $K_7$ should be set to zero. Of course this may not be true close to the plant nor for large solid shielding obstacles which may then be classed as barriers.

As the formulas use third order polygons with large constants, their border value for the distance 0 meters would be constant. There fore the formulas are only valid for distances greater than or equal to 100 meters. As there is no guarantee that the formulas are not used at smaller distances, here we extrapolate the formulas for the area between zero and 100 meters. the value at the distance is set to zero and the value at 100 meter is calculated using the formulas. Values between 0 and 100 meters was calculated with linear interpolation.

### 3.2.3 ISO-9613-2 NOISE PREDICTION MODEL

In this model, the equivalent continuous downwind octave-band sound pressure level at a receiver, $L_{fT}$, shall be calculated for each point source, and its image sources, and for the eight octave bands with octave band center frequencies varying from 63 Hz to 8 kHz, using Eqns. 3.9 and 3.10:

$$L_{ft}(DW) = \ L_w + D_c - A \tag{3.9}$$

In Eqns (3.9) and (3.10), $L_w$ is the octave-band sound power level, in decibels, produced by the point sound source relative to a reference sound power of one picowatt (1pW). $D_c$ is the directivity correction, in decibels and A is the octave-band attenuation, in decibels, that occurs during propagation from the point sound source to the receiver.

The equivalent continuous A-weighted downwind sound pressure level may be obtained by summing the contributing time-mean-square sound pressures calculated according to Eqn. 3.9. For each point source, for each of their image sources, and for each octave band, as specified by the following equation [10, 11, 18, 25].

$$L_{AT}(DW) = 10 \log \left\{ \sum_{i=1}^{n} \left[ \sum_{j=1}^{8} 10^{0.1\left[L_{ft}(ij)+A_f(j)\right]} \right] \right\} \tag{3.10}$$

where n is the number of contributions i (sources and paths), j is an index indicating the eight standard octave- band mid-band frequencies from 63 Hz to 8 kHz; $A_f$ denotes the standard A-weighting.

The long-term average A-weighted sound pressure level

$$L_{AT}(LT) \;=\; L_{AT}(DW) \;-\; C_{met} \tag{3.11}$$

Where $C_{met}$ is the meteorological correction.The attenuation term A in equation is given by

$$A \;=\; A_{div} \;+\; A_{atm} \;+ A_{gr} \;+ A_{bar} \;+ A_{misc} \tag{3.12}$$

where $A_{div}$ is the attenuation due to geometrical divergence, $A_{atm}$ is attenuation due to atmospheric absorption, $A_{gr}$ is attenuation due to ground condition, $C_{met}$ is meteorological correction, $A_{bar}$ is attenuation due to barrier and $A_{misc}$ is the attenuation due to miscellaneous other effects (attenuation due to vegetation and attenuation due to industrial sites and attenuations due to housing etc.). These attenuations factors were calculated as per the standard guidelines. Following are the attenuation factors calculated in the ISO-9613-2 model

#### 3.2.3.1 Geometrical Divergence

For a point source of a spherical wave the geometrical divergence is predicted by

$$A_{div} \;=\; \left[20 \log(d/d_0) \;+\; 11\right] \tag{3.13}$$

Where d is the distance from the source to receiver, in meters; d is the reference distance (=1m).

#### 3.2.3.2 Atmospheric Absorption

The attenuation due to atmospheric absorption $A_{atm}$, in decibels, during propagation through a distance d, in meters, is given by following equation:

$$A_{atm} \;=\; \alpha\, d/1000 \tag{3.14}$$

Where $\alpha$ is the atmospheric attenuation coefficient, in decibels per kilometer, for each octave band at the midband frequency. The frequency-dependent atmospheric attenuation is predicted using expressions detailed in ISO-9613-1.

#### 3.2.3.3 Ground Attenuation

Ground attenuation results from the interference between sound reflected from the ground surface and the sound propagating directly between the source and receiver. ISO-9613-2 specifies three distinct regions for ground attenuation (see Fig. 3.2).

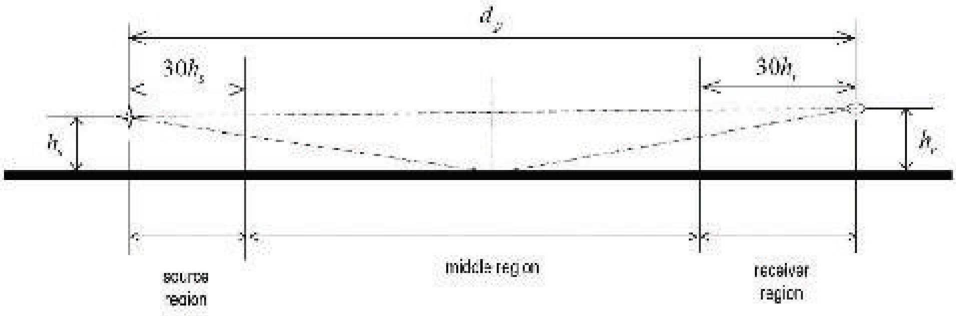



Figure 3.2: On the calculation of the ground attenuation in ISO 9613-2

The source region stretching over a distance $30h_s < d_p$ from the source towards the receiver

The receiver region, stretching over a distance $30h_r < d_p$.

A middle region, stretching over the distance between the source and receiver regions. If $d_p < (30h_r + 30h_s)$, the source and receiver regions will overlap, and there is no middle region.

The acoustic properties of each ground region are specified by a ground factor G. Three categories of reflecting surface are specified:

- hard ground (G=0): paving, water, ice, concrete and other surfaces with low porosity
- porous ground (G = 1): grassland, trees, vegetation, farm land
- mixed ground ( 0 < G < 1): mixture of hard and porous ground.

The combined ground effect is calculated by

$$A_{gr} = A_s + A_r + A_m \tag{3.15}$$

where $A_s$, $A_r$ and $A_m$ are the source, receiver and middle region components of the attenuation with corresponding ground factors $G_s$, $G_r$ and $G_m$. These values are defined using the expressions provided ISO-9613-2.

Alternatively, for some specific conditions when much of the ground is porous and the sound is not a pure tone, the ground attenuation can be calculated by the formula

$$A_{gr} = 4.8 - (2h_m/d)(17 + 300/d), dB \tag{3.16}$$

where $h_m$ is the mean height of the propagation path above the ground. In this case the directivity correction is given by:

$$D = 10\log\{1 + [d_p^2 + (h_s - h_r)^2]/[d_p^2 + (h_s + h_r)^2]\}dB \tag{3.17}$$

Where $d_p$ is the distance between source and receiver, $h_s$ is the height of the source and $h_r$ is the height of the receiver. This directivity correction accounts for the increase in sound power level of the source due to reflections from the ground near the source.

#### 3.2.3.4 Meteorological Correction

A long-term average A-weighted sound pressure level requires to include the effect of a variety of meteorological conditions, which can be favorable or unfavorable for sound propagation. This is accounted for by the meteorological correction term whose value is predicted from

$$C_{met} \;=\; 0 \;\; if\, d_p \;\leq\; 10\,(h_s + h_r) \tag{3.18}$$

$$C_{met} \;=\; C_0\,[1 - 10\,(h_s + h_r)/d_p] \;\; if\, d_p \;>\; 10\,(h_s + h_r) \tag{3.19}$$

Where $h_s$ is the source height, in meters, $h_r$ is the receiver height, in meters and $d_p$ is the distance between the source and receiver projected to the horizontal ground plane, in metres. $C_0$ is a factor, in decibels, which depends on local meteorological statistics for wind speed and direction, and temperature gradients. Typical values are $0 \leq C_0 \leq 5$.

NORDFORSK [138] noise model (developed by Lydteknisk Laboratorium of Denmark (now it is changed to DELTA ACOUSTIC and VIBRATION) in 1982 for the Danish Environmental Protection Agency) and VDI-2720 [139] (Extended version of VDI-2714 developed by Verein Deutscher Ingenieur, Germany in 1986)are similar to ISO-9613-2. Calculation of all attenuation factors of both the models were similar to ISO-9613-2, except the calculation of atmospheric attenuation in NORDFORSK model. For NORDFORSK model, the calculation of atmospheric attenuation was calculated as per ANSI S1.26 - 1978. For VDI-2720, the atmospheric attenuation was calculated as per ISO-9613-1.

### 3.2.4 ENM - ENVIRONMENTAL NOISE MODEL

The Environmental Noise Model (ENM) was developed by RTA Technology Pty Ltd. in 1985 [9, 18, 140]. The basic format of calculation is as follows;

$$L_p = \sum_{all\ sources}^{\log} (L_w + D - A_1 - A_2 - A_3 - A_4 - A_5) \tag{3.20}$$

where, $L_w$= sound power level $dB$ re $10^{-12}$ watts,

$D$= source directivity,
$A_1$ = geometric spreading,
$A_2$= barrier attenuation
$A_3$ = air absorption
$A_4$ = wind and temperature effects
$A_5$ = ground attenuation

ENM follows generally the methods used in CONCAWE. Where the two models deviate is in the extent of usage of theory ENM being a relatively new model takes advantage of recent developments in the theory of ground effect and the effect of meteorology. The other notable difference is that ENM was produced as a computer program rather than a descriptive set of algorithms. ENM works in both $1/3^{rd}$octave and 1/1 octave format from *25Hz to 20kHz*.

#### 3.2.4.1 Sound Power Level ($L_w$)

The ENM program allows sources to be enclosed or unenclosed. If the source is unenclosed then the sound power level is specified in the normal way. If the source (or a group of sources) is enclosed then one needs to specify both the sound power levels of the sources and the acoustic properties of the enclosure walls. Enclosures are defined as a collection of rectangular surfaces with an absorptive face on the side nearest the source and having a sound transmission loss. The total sound pressure level inside the enclosure and close to the surface is:

$$L_{p,inside} = L_{W,totatl} + 10\log\left[\frac{Q}{4\pi r^2} + \frac{4}{Abs}\right] \tag{3.21}$$

where $\frac{Q}{4\pi r^2}$ is the directed field term and is approximately the reciprocal of the sum of all the surface areas comprising the enclosure and **Abs** is the total absorption within the enclosure and is obtained by summing the absorption of all surfaces comprising the enclosure.

#### 3.2.4.2 Directivity Correction

A frequency independent directivity correction term is included in the ENM model and is based on either user-selected angles or array co-ordinates recommended in ISO 3745-1977. These co-ordinates are points on the surface of a hypothetical sphere whose center coincides with the acoustic center of the source. The program interpolates values for directions of source to receiver which do not coincide with these array co-ordinates.

#### 3.2.4.3 Geometric Spreading ($A_1$)

All sources are considered first in the absence of the ground, that is, as if they were suspended in a free field. Sources are of three types: point, line and plane.

For point sources, the attenuation due to geometric spreading is that for spherical radiation.

$$A_1^{point} = 10\ \log\left(4\pi R^2\right) \tag{3.22}$$

For line sources, the attenuation due to geometric spreading is that source of length L is

$$A_1^{line} = 10\ \log\left(4\pi al/\alpha\right) \tag{3.23}$$

Where, L is the source length , a is the perpendicular separation of the receiver from the line source axis and, $\alpha$ is the subtended angle in radians. For plane sources, the sound pressure resulting from monopole radiation of a rectangular source of area A is

$$p^2 = \iint\limits_A \left(W_{\rho c}/A\right).\left\{1/\left(4\pi R^2\right)\right\} dxdy \tag{3.24}$$

Where, $W$ the total source power and $\rho c$ is the characteristic impedance of air measured at a point which is a distance $R$ from the source acoustic center. The integration was performed numerically for different sized sources and for different angles subtended with the plane. Variation of pressure with angle and plane aspect ratio was shown not to vary significantly for most situations and so the results were condensed into a single non-dimensionalised curve shown in ENM literature. The attenuation for plane sources is then calculated by determining the value of $C$ and hence,

$$A_1^{point} = 10\ \log\left(4\pi R^2\right)\ +\ C \tag{3.25}$$

#### 3.2.4.4 Barrier Attenuation ($A_2$)

In ENM noise prediction model, the Maekawa theory is commonly used for predicting noise reduction from barriers. Similar procedure was followed in CONCAWE noise prediction model.

#### 3.2.4.5 Air Absorption ($A_3$)

The algorithm for the calculation of air absorption is based on ANSI (American National Standards Institute) S1.26.17. The same standard was used in CONCAWE model. ENM program calculates the value of air absorption in octave band frequencies.

#### 3.2.4.6 Wind and Temperature Effects ($A_4$)

The effects of refraction of sound in the atmosphere can best be thought of in terms of sound ray propagation. Curvature of sound ray paths is a result of variations in the speed of sound with height. Sound speed variations can either be caused by changes in air density due to temperature or simply by the movement of the air medium itself.

Intuitively, one would expect that sonic speed variations caused by a combination of these two effects would be additive. Examination of measurements conducted by Parkin and Scholes shows there is some evidence to support this theory. This principle is assumed in the CONCAWE model as well. Table 3.6 shows the value of attenuation so obtained for two source-receiver distances.

Table 3.6: Excess Attenuation due to Wind and Temperature Effect

| VALUES OF EXCESS ATTENUATION $A_4$ DUE TO WIND AND TEMPERATURE EFFECTS | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| TOTAL VERTICAL SONIC GRADIENT | FREQUENCY | | | | | | | | | |
| | 31.5 | 63 | 125 | 250 | 500 | 1k | 2k | 4k | 8k | 16k |
| **110 metres** | | | | | | | | | | |
| +0.075 | -2 | -2 | -0.5 | 3 | -2 | -5 | -2 | -2 | -2 | -2 |
| -0.075 | 1 | 1 | 2.5 | 0 | 2 | 6 | 10 | 6 | 6 | 6 |
| **616 metres** | | | | | | | | | | |
| +0.075 | -5 | -5 | -2 | 0 | -9 | -9 | -6 | -7 | -7 | -7 |
| -0.075 | 5 | 5 | 6 | 4 | 7 | 7 | 7 | 6 | 6 | 6 |

#### 3.2.4.7 Ground Attenuation ($A_5$)

Propagation of sound from a source placed above a semi-infinite ground plane has been extensively reviewed. The expression of the plane wave reflection coefficient $R_p$ may be written as:

$$R_p = \frac{\left[sin\ \phi - \left(\frac{\rho c}{Z_g}\right)\right]}{\left[sin\ \phi + \left(\frac{\rho c}{Z_g}\right)\right]} \tag{3.26}$$

where $\rho c$ is the characteristic impendence of air, 407 MKS Rayls and $Z_g$ is the impendence of the ground surface and is given by

$$Z_g = \rho c \left[1 + 0.0571 \left(\frac{\rho f}{\phi}\right)^{-0.754} - i0.087 \left(\frac{\rho f}{\phi}\right)^{-0.732}\right] \tag{3.27}$$

where $f$ is the frequency and $\phi$ is the ground surface flow resistivity.

## 3.3 Study Area

For this present study two mines (Balram Opencast Coal Mine, Talcher and Panchpatmali Bauxite Mine, NALCO, Koraput) were chosen from Odisha. Fig. 3.3 represents geographical map of Odisha with the location map (District wise) of Balram Opencast Coal Mine (Talcher Coal Field, Talcher, Angul District) and Panchpatmali Bauxite Mine (Nalco, Damonjodi, Koraput District).

### 3.3.1 Balram Opencast Coal Mine

The Balram Opencast Project (previously known as Kalinga OCP) was operated first on $27^{th}$ January, 1991. The mine is situated near Danara village of Angul District in Odisha and located in South Central part of Talcher Coalfields. It's Longitude is 85°02′52″E and Latitude of 20°56′02″N to 20°58′28″N. Figure 3.4 represents the geographical map of Talcher coalfield, and Fig. 3.5 shows the map of Balram Opencast mines.

Geological exploration has been done by drilling in an area of 23.78 sq kms. The block is geotechnically complicated, as 21 normal faults have traversed the area. The total coal reserve in the entire block is estimated at 980 MT. However the present Balram east block amounts to only 168 MT. of coal occurring in seam II, III & IV. In general the strike of the bed is East West and the beds dip gently 20 to 90 in northerly direction. Due to presence of a number of splits and variable parting thickness, shovel and dumper combination is proved suitable for removal of overburden (OB) and coal. At present 10 $m^3$ shovels with 85 T dumpers are used for OB removal. Pay loader with 10 wheeler tippers are deployed for coal production. Fig. 3.6 represents the selected machineries for the current study.

### 3.3.2 Panchpatmali Bauxite Mine

Panchpatmali bauxite mine is situated in village Damanjodi, in Koraput district of Odisha, India. The Alumina refinery at Damanjodi is situated at about 16 km from Panchpatmali Bauxite mines. Damanjodi is about 12 km. Its the Latitude of 18°51′0″N and Longitude of 83°1′6″E. The Panchpatmali bauxite deposit is a high level lateritic deposit situated in the Eastern Ghats, at an altitude of 1300 m above M.S.L. on a plateau covering 17 sq.km area. This plateau rises 300m-400m above the plane of the surrounding hilly terrain of undulating topography. Panchpatmali bauxite deposit is the one amongst a series of bauxite deposits which were discovered in the east coast region of India in early 1960s to put India in the $5^{th}$ position in the world's bauxite map with a total bauxite reserves of over 2 billion tonnes. The current annual production is about 4.8 million tonnes which is now under expansion to 6.3 MT. Considering its vast deposit containing over 300 million tonnes of reserve, Panchpatmali bauxite deposit under the name of NALCO Ltd., was picked up by Govt. of India as a front-runner for the bauxite exploitation in the eastern region of India.Fig.3.7 represent the satellite map of Panchpatmali Bauxite Mine, where as Fig. 3.8 depicts the working map.Fig. 3.9 represents the selected machineries used in the mine.

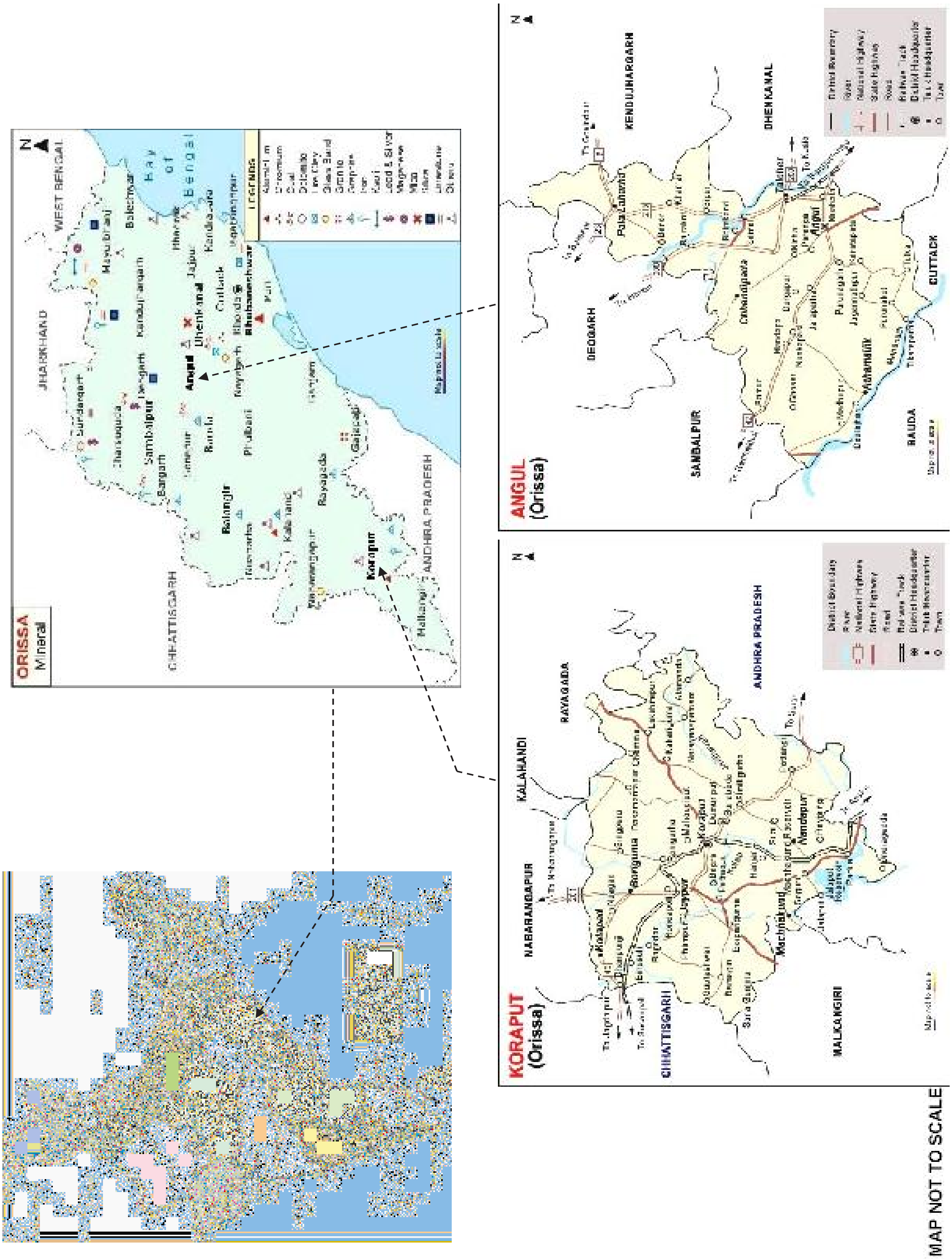



Figure 3.3: Location map of the study areas

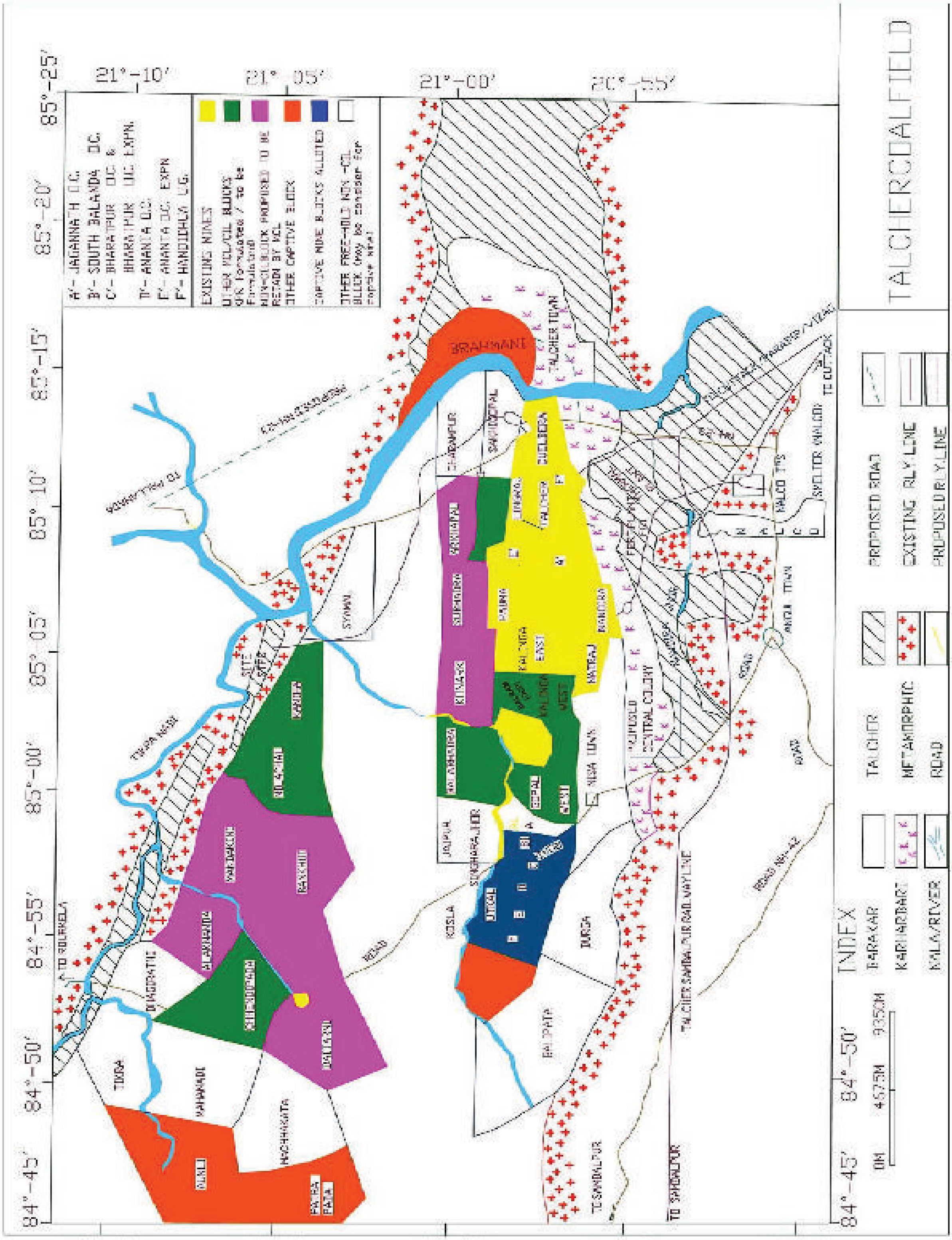



Figure 3.4: Geographical map of Talcher Coalfield.

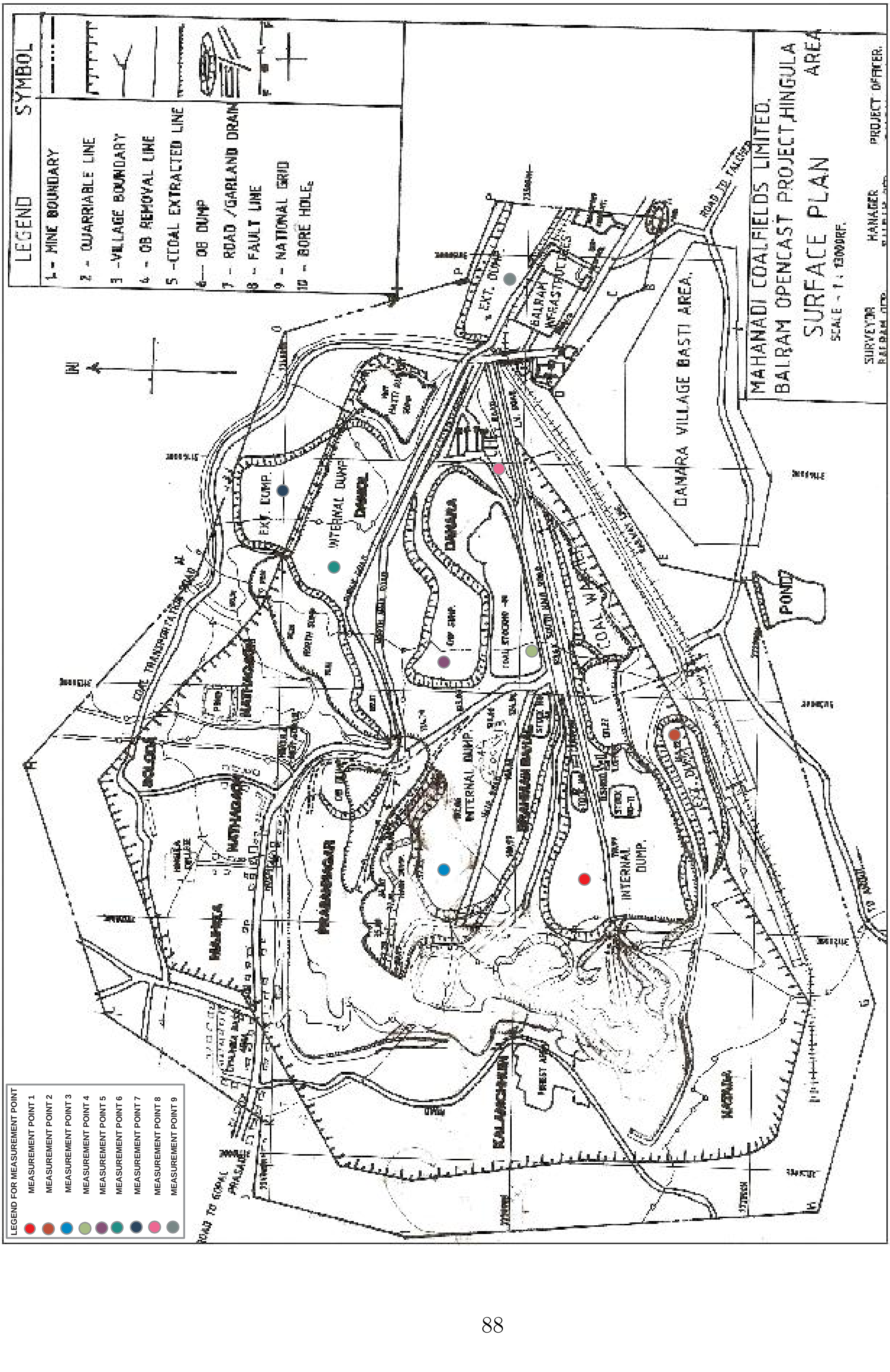



Figure 3.5: Working map of Balram MCL coal mine.

(a) Grader (220 hp)


(b) Dumper (85T)


(c) Shovel (10 $m^3$ bucket capacity)

(d) Tipper (10T-160hp)

(e) Dozer (410hp)

Figure 3.6: Machineries used in Balram opencast coal mine

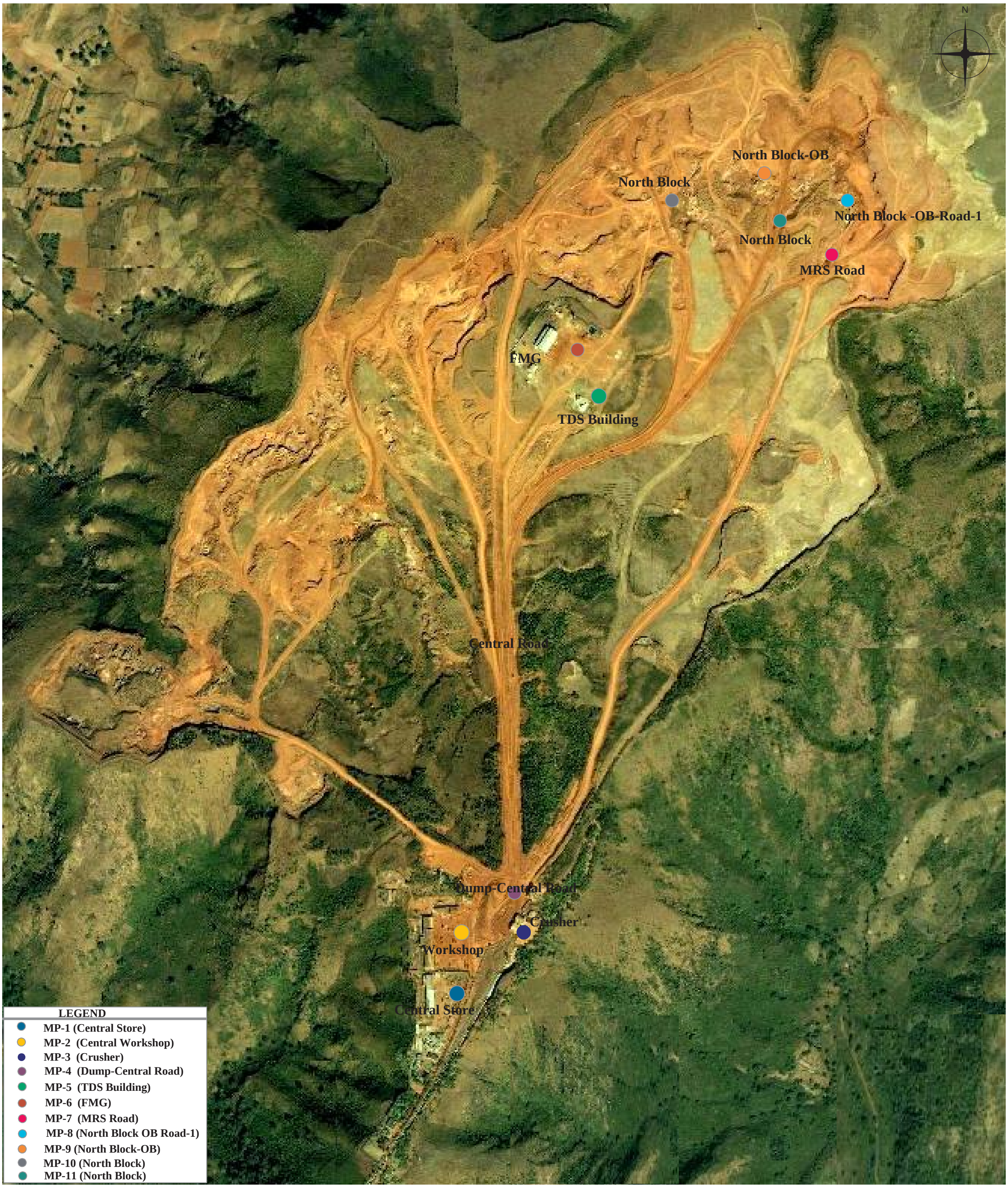



Figure 3.7: Panchpatmali bauxite mine,NALCO [141].

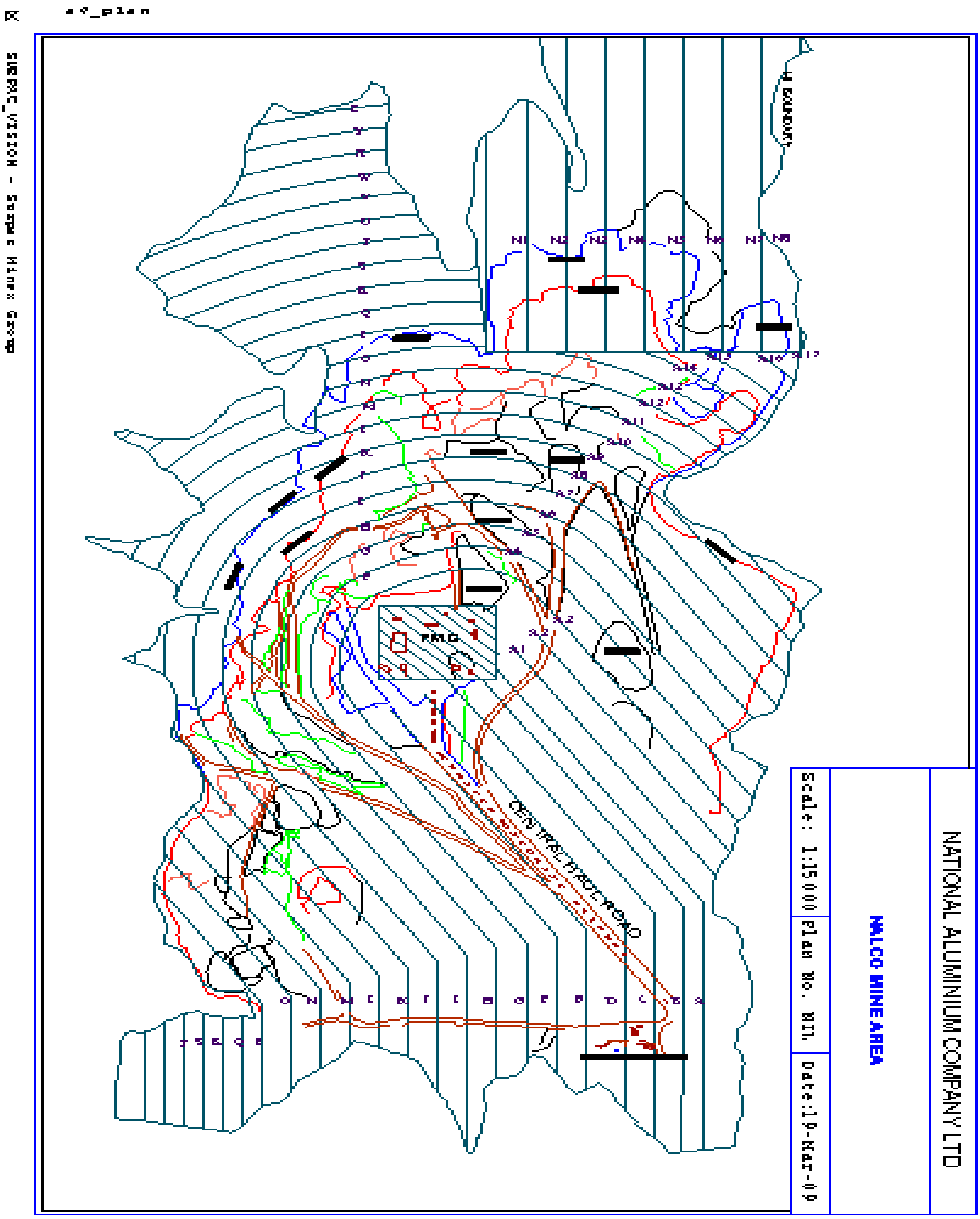



Figure 3.8: Working Map of Panchpatmali bauxite mine, NALCO

(a) Percussive Drill (324 hp)

(b) Dozer (416 hp)

(c) Dumper (50T)

(d) Pay-Loader(555hp)


(e) Rock-breaker (120 hp)


(f) Shovel ($3m^3$ bucket capacity, 320 hp)

Figure 3.9: Machineries used in Panchpatmali bauxite mine, NALCO

## 3.4 Machinery Noise Prediction in Opencast Mines

In the present work, statistical noise prediction models viz. VDI-2714, CONCAWE, ISO-9613-2, VDI-2720, NORDFORSK and ENM etc. were used to predict noise of opencast mining machineries.

VDI-2714 is used to predict Balram opencast mining machineries noise. For Balram opencast mine, shovel (10 $m^3$ bucket capacity), dozer (410hp), tipper (10T-160hp), grader (220 hp) and dumper (85T) were selected for this work.

Other frequency dependent prediction models (CONCAWE, ISO-9613-2 etc.) are discussed in this section. For Panchpatmali bauxite mine, dozer (416 hp), shovel (3$m^3$ bucket capacity, 320 hp), pay-loader (555hp), dumper (50T), rock-breaker (120 hp), rotary percussive drill (324 hp), double roll toothed crusher were selected. Three major frequency dependent models (CONCAWE, ISO-9613-2 and ENM) were used to predict Panchpatmali bauxite mining machineries noise for 50 m, 100 m and 150 m distances. The calculation and prediction results are described as follows:

### 3.4.1 Application of ISO-9613-2 Noise Prediction Model

Using the Equation 3.9, ISO-9613-2 model was applied to predict the machineries noise of Panchaptmali opencast bauxite mine, NALCO. For ISO-9613-2, all the calculations were made in the frequency range between 63 Hz to 8000 Hz. Attenuation factors, DI (Directive Index), $K_1$(Geometrical divergence), $K_2$(atmospheric absorption), $K_3$ (ground condition) , $K_4$ (meteorological correction) are calculated as per the standard. As this mine is covered with hilly area, with the geographical condition of mines and as per the standard, $K_5$ (barrier attenuation) and $K_6$ (attenuation due to miscellaneous effects) are considered as zero. All the attenuation factors were calculated as per the standard and finally the predicted SPL was calculated in dB(A) using A-weighting correction. Table 3.7 represents the ISO-9613-2 prediction results for dozer (416 hp) at 50 m, 100 m and 150 m , where as Fig.3.10 represents the spectrum analysis. Table 3.8 to Table 3.13 represents the prediction results (ISO-9613-2) of other selected machineries at 50 m, 100 m and 150 m. Figure 3.11 to 3.16 represents sound spectrum analysis of all the selected machineries with ISO-9613-2 prediction assessment. After getting the prediction results, contour plots was generated and represented in Fig. 3.17. From the contour plot, noise mapping is possible to study.

Table 3.7: ISO-9613-2 results for Dozer machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 82.1 | 77.8 | 76.8 | 75.9 | 71.7 | 69.2 | 68.1 | 56.7 | **77.8** |
| | $L_W$ (Measured) | 127 | 122.7 | 121.7 | 120.8 | 116.6 | 114.1 | 113 | 101.6 | **122.7** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.1680 | 0.3645 | 0.6100 | 1.1700 | 3.2350 | |
| | $K_3$ | -3 | -0.670 | 1.929 | 0.142 | -1.290 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 | |
| | DI - $\Sigma$ K | 42.268 | 44.609 | 47.248 | 45.574 | 44.338 | 44.374 | 44.934 | 46.9 | |
| | $L_P$ (Predicted) | 84.731 | 78.090 | 74.451 | 75.225 | 72.261 | 69.725 | 68.065 | 54.6 | **77.7** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 73.6 | 72.4 | 71.3 | 70.6 | 66.3 | 62.6 | 60.4 | 50.2 | **72.0** |
| | $L_W$ (Measured) | 124.6 | 123.4 | 122.3 | 121.6 | 117.3 | 113.6 | 111.4 | 101.2 | **123.0** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.1090 | 0.3360 | 0.7290 | 1.2200 | 2.3400 | 6.4700 | |
| | $K_3$ | -3. | -0.3 | 3.190 | 0.746 | -1.214 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.65 | 1.65 | 1.65 | 1.65 | 1.65 | 1.65 | 1.65 | 1.65 | |
| | DI - $\Sigma$ K | 49.7222 | 52.4442 | 56.0141 | 53.7970 | 52.2296 | 52.4346 | 53.5546 | 57.6846 | |
| | $L_P$ (Predicted) | 74.8778 | 70.9558 | 66.2859 | 67.8030 | 65.0704 | 61.1654 | 57.8454 | 43.5154 | **69.8** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 69.2 | 67.6 | 65.4 | 64.2 | 61.2 | 56.7 | 55.1 | 46.2 | **66.3** |
| | $L_W$ (Measured) | 123.7 | 122.1 | 119.9 | 118.7 | 115.7 | 111.2 | 109.6 | 100.7 | **120.8** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.5040 | 1.0935 | 1.8300 | 3.5100 | 9.7050 | |
| | $K_3$ | -3.3 | -0.220 | 3.504 | 0.818 | -1.335 | -1.65 | -1.65 | -1.65 | |
| | $K_4$ | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | |
| | DI - $\Sigma$ K | 53.3760 | 56.4882 | 60.3327 | 57.9873 | 56.4224 | 56.8446 | 58.5246 | 64.7196 | |
| | $L_P$ (Predicted) | 70.324 | 65.611 | 59.567 | 60.712 | 59.277 | 54.355 | 51.075 | 35.980 | **63.3** |

Table 3.8: ISO-9613-2 results for Shovel machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 81.7 | 79.3 | 76.6 | 74.3 | 70.2 | 69.2 | 67.7 | 65.6 | **77.2** |
| | $L_W$ (Measured) | 126.6 | 124.2 | 121.5 | 119.2 | 115.1 | 114.1 | 112.6 | 110.5 | **122.1** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.1680 | 0.3645 | 0.6100 | 1.1700 | 3.2350 | |
| | $K_3$ | -3 | -0.535 | 1.622 | 0.087 | -1.291 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.968 | 44.444 | 46.641 | 45.220 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 84.631 | 79.755 | 74.858 | 73.979 | 71.062 | 70.025 | 67.965 | 63.800 | **77.4** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 72.7 | 71.2 | 69.3 | 67.5 | 64.9 | 63.3 | 62.7 | 52.8 | **71** |
| | $L_W$ (Measured) | 123.7 | 122.2 | 120.3 | 118.5 | 115.9 | 114.3 | 113.7 | 103.8 | **122** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.1090 | 0.3360 | 0.7290 | 1.220 | 2.340 | 6.470 | |
| | $K_3$ | -3 | -0.121 | 2.771 | 0.671 | -1.214 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | |
| | DI - $\Sigma$ K | 49.572 | 52.472 | 55.444 | 53.572 | 52.079 | 52.284 | 53.404 | 57.534 | |
| | $L_P$ (Predicted) | 74.127 | 69.727 | 64.855 | 64.927 | 63.821 | 62.015 | 60.295 | 46.265 | **69** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 67.7 | 66.3 | 65.3 | 62.4 | 59.8 | 58.2 | 57.2 | 47.2 | **65.9** |
| | $L_W$ (Measured) | 122.2 | 120.8 | 119.8 | 116.9 | 114.3 | 112.7 | 111.7 | 101.7 | **120.4** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.5040 | 1.0935 | 1.8300 | 3.510 | 9.705 | |
| | $K_3$ | -3 | 0.115 | 3.193 | 0.886 | -1.186 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | |
| | DI - $\Sigma$ K | 53.576 | 56.724 | 59.921 | 57.955 | 56.471 | 56.894 | 58.574 | 64.769 | |
| | $L_P$ (Predicted) | 68.624 | 64.075 | 59.878 | 58.944 | 57.828 | 55.805 | 53.125 | 36.930 | **62.9** |

Table 3.9: ISO-9613-2 results for Dumper machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 75.2 | 74.5 | 73.6 | 72.6 | 68.7 | 66.8 | 65.8 | 63.6 | **75.1** |
| | $L_W$ (Measured) | 120.1 | 119.4 | 118.5 | 117.5 | 113.6 | 111.7 | 110.7 | 108.5 | **120** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.1680 | 0.3645 | 0.6100 | 1.1700 | 3.2350 | |
| | $K_3$ | -3 | -0.342 | 1.159 | 0.072 | -1.291 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.968 | 44.637 | 46.178 | 45.204 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 78.131 | 74.763 | 72.321 | 72.295 | 69.562 | 67.625 | 66.065 | 61.800 | **75.3** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 71.2 | 69.6 | 69.2 | 68.2 | 66.7 | 64.6 | 62.4 | 54.8 | **71.9** |
| | $L_W$ (Measured) | 122.2 | 120.6 | 120.2 | 119.2 | 117.7 | 115.6 | 113.4 | 105.8 | **122.9** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.1090 | 0.3360 | 0.7290 | 1.2200 | 2.3400 | 6.4700 | |
| | $K_3$ | -3 | 0.133 | 2.137 | 0.650 | -1.214 | -1.5 | 1.5 | -1.5 | |
| | $K_4$ | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | 1.2 | |
| | DI - $\Sigma$ K | 49.2722 | 52.4281 | 54.5110 | 53.2512 | 51.7789 | 51.9846 | 53.1046 | 57.2346 | |
| | $L_P$ (Predicted) | 72.9 | 68.1 | 65.6 | 65.9 | 65.9 | 63.6 | 60.3 | 48.5 | 70.4 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 63.6 | 62.2 | 60.3 | 57.8 | 54.9 | 52.6 | 51.5 | 40.1 | **60.8** |
| | $L_W$ (Measured) | 118.4 | 117.0 | 115.1 | 112.6 | 109.7 | 107.4 | 106.3 | 94.9 | **115.6** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0118 | 0.0459 | 0.1690 | 0.5208 | 1.1300 | 1.8910 | 3.6270 | 10.0285 | |
| | $K_3$ | -3 | 0.400 | 2.517 | 0.8752 | -1.184 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.8387 | 1.8387 | 1.8387 | 1.8387 | 1.8387 | 1.8387 | 1.8387 | 1.8387 | |
| | DI - $\Sigma$ K | 53.7151 | 57.1500 | 59.3895 | 58.0993 | 56.6484 | 57.0943 | 58.8303 | 65.2318 | |
| | $L_P$ (Predicted) | 64.6 | 59.8 | 55.7 | 54.5 | 53.0 | 50.3 | 47.4 | 29.6 | **58.0** |

Table 3.10: ISO-9613-2 results for Pay-Loader machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 84.2 | 79.6 | 78.7 | 73.2 | 72.4 | 68.7 | 66.6 | 59.6 | 77.5 |
| | $L_W$ (Measured) | 129.1 | 124.5 | 123.6 | 118.1 | 117.3 | 113.6 | 111.5 | 104.5 | 122.4 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.054 | 0.168 | 0.364 | 0.610 | 1.17 | 3.235 | |
| | $K_3$ | -3 | -0.4201 | 1.3638 | 0.0746 | -1.2914 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - Σ K | 41.968 | 44.559 | 46.382 | 45.207 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 87.131 | 79.940 | 77.217 | 72.892 | 73.262 | 69.525 | 66.865 | 57.8 | 77.7 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 73.8 | 72.7 | 69.6 | 66.7 | 65.3 | 62.4 | 55.2 | 48.2 | 70 |
| | $L_W$ (Measured) | 124.8 | 123.7 | 120.6 | 117.7 | 116.3 | 113.4 | 106.2 | 99.2 | 121 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.1090 | 0.3360 | 0.7290 | 1.220 | 2.340 | 6.470 | |
| | $K_3$ | -3 | 0.0315 | 2.417 | 0.6539 | -1.2147 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.35 | 1.35 | 1.35 | 1.35 | 1.35 | 1.35 | 1.35 | 1.35 | |
| | DI - Σ K | 49.422 | 52.475 | 54.941 | 53.404 | 51.928 | 52.134 | 53.254 | 57.384 | |
| | $L_P$ (Predicted) | 75.377 | 71.224 | 65.659 | 64.295 | 64.371 | 61.265 | 52.945 | 41.815 | 68.4 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150 m | $L_P$ (Measured) | 70.1 | 68.6 | 60.7 | 57.3 | 51.6 | 50.4 | 44.8 | 40.2 | **59.8** |
| | $L_W$ (Measured) | 124.6 | 123.1 | 115.2 | 111.8 | 106.1 | 104.9 | 99.3 | 94.7 | **114.3** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.504 | 1.093 | 1.830 | 3.510 | 9.705 | |
| | $K_3$ | -3 | 0.275 | 2.805 | 0.867 | -1.186 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.9 | 1.9 | 1.9 | 1.9 | 1.9 | 1.9 | 1.9 | 1.9 | |
| | DI - Σ K | 53.476 | 56.784 | 59.433 | 57.835 | 56.371 | 56.794 | 58.474 | 64.669 | |
| | $L_P$ (Predicted) | 71.124 | 66.315 | 55.766 | 53.964 | 49.728 | 48.105 | 40.825 | 30.030 | **57** |

Table 3.11: ISO-9613-2 results for Rock Breaker machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 77.4 | 74.8 | 70.6 | 69.3 | 68.6 | 67.1 | 66.2 | 57.5 | 74.1 |
| | $L_W$ (Measured) | 122.3 | 119.7 | 115.5 | 114.2 | 113.5 | 112.0 | 111.1 | 102.4 | 119 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.1680 | 0.3645 | 0.610 | 1.170 | 3.235 | |
| | $K_3$ | -3 | -0.535 | 1.622 | 0.0876 | -1.2914 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.968 | 44.444 | 46.641 | 45.220 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 80.331 | 75.255 | 68.858 | 68.979 | 69.462 | 67.925 | 66.465 | 55.700 | 74.6 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 70.1 | 69.4 | 65.3 | 64.2 | 62.1 | 61.6 | 60.4 | 51.2 | 68.4 |
| | $L_W$ (Measured) | 121.1 | 120.4 | 116.3 | 115.2 | 113.1 | 112.6 | 111.4 | 102.2 | 119.4 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.109 | 0.336 | 0.729 | 1.220 | 2.340 | 6.470 | |
| | $K_3$ | -3 | -0.1213 | 2.771 | 0.671 | -1.214 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | |
| | DI - $\Sigma$ K | 49.572 | 52.472 | 55.444 | 53.572 | 52.079 | 52.284 | 53.404 | 57.534 | |
| | $L_P$ (Predicted) | 71.527 | 67.927 | 60.855 | 61.627 | 61.021 | 60.315 | 57.995 | 44.665 | 66.5 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 65.4 | 63.2 | 59.7 | 59.2 | 57.2 | 56.2 | 55.3 | 46.5 | 63.2 |
| | $L_W$ (Measured) | 119.9 | 117.7 | 114.2 | 113.7 | 111.7 | 110.7 | 109.8 | 101.0 | 117.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.504 | 1.0935 | 1.830 | 3.510 | 9.705 | |
| | $K_3$ | -3 | 0.1157 | 3.193 | 0.8865 | -1.1864 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | |
| | DI - $\Sigma$ K | 53.576 | 56.724 | 59.921 | 57.955 | 56.471 | 56.894 | 58.574 | 64.769 | |
| | $L_P$ (Predicted) | 66.324 | 60.975 | 54.278 | 55.744 | 55.228 | 53.805 | 51.225 | 36.230 | 60.3 |

Table 3.12: ISO-9613-2 results for Drill machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 78.8 | 76.2 | 73.6 | 72.6 | 70.1 | 66.8 | 67.2 | 65.6 | 75.9 |
| | $L_W$ (Measured) | 123.7 | 121.1 | 118.5 | 117.5 | 115.0 | 111.7 | 112.1 | 110.5 | 120.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.1680 | 0.3645 | 0.610 | 1.170 | 3.235 | |
| | $K_3$ | -3 | -1.253 | 0.719 | 0.0718 | -1.2914 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.968 | 43.726 | 45.739 | 45.204 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 81.731 | 77.373 | 72.761 | 72.295 | 70.962 | 67.625 | 67.465 | 63.800 | 76.1 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 74.5 | 74.3 | 72.3 | 67.4 | 67.1 | 65.6 | 64.3 | 51.2 | 72.8 |
| | $L_W$ (Measured) | 125.5 | 125.3 | 123.3 | 118.4 | 118.1 | 116.6 | 115.3 | 102.2 | 123.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.109 | 0.336 | 0.729 | 1.220 | 2.340 | 6.470 | |
| | $K_3$ | -3 | -1.120 | 1.536 | 0.650 | -1.214 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.072 | 49.973 | 52.710 | 52.050 | 50.578 | 50.784 | 51.904 | 56.034 | |
| | $L_P$ (Predicted) | 77.427 | 75.326 | 70.589 | 66.349 | 67.521 | 65.815 | 63.395 | 46.165 | 72.5 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 71.2 | 70.2 | 64.2 | 57.2 | 51.3 | 54.3 | 44.9 | 42.6 | 61.6 |
| | $L_W$ (Measured) | 125.7 | 124.7 | 118.7 | 111.7 | 105.8 | 108.8 | 99.4 | 97.1 | 116.1 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.504 | 1.093 | 1.830 | 3.510 | 9.705 | |
| | $K_3$ | -3 | -1.0112 | 1.8370 | 0.8628 | -1.1864 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | |
| | DI - $\Sigma$ K | 52.076 | 54.097 | 57.065 | 56.431 | 54.971 | 55.394 | 57.074 | 63.269 | |
| | $L_P$ (Predicted) | 73.624 | 70.602 | 61.634 | 55.268 | 50.828 | 53.405 | 42.325 | 33.830 | 60.5 |

Table 3.13: ISO-9613-2 results for Crusher machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 76.8 | 74.1 | 72.9 | 71.6 | 68.7 | 66.0 | 58.6 | 55.5 | 73.8 |
| | $L_W$ (Measured) | 121.7 | 119.0 | 117.8 | 116.5 | 113.6 | 110.9 | 103.5 | 100.4 | 118.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0038 | 0.0148 | 0.0545 | 0.168 | 0.364 | 0.610 | 1.170 | 3.235 | |
| | $K_3$ | -3 | -1.253 | 0.719 | 0.071 | -1.291 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.968 | 43.726 | 45.739 | 45.204 | 44.037 | 44.074 | 44.634 | 46.699 | |
| | $L_P$ (Predicted) | 79.731 | 75.273 | 72.061 | 71.295 | 69.562 | 66.825 | 58.865 | 53.7 | 74.2 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 69.8 | 67.7 | 65.9 | 64.2 | 61.7 | 57.8 | 52.7 | 48.1 | 66.5 |
| | $L_W$ (Measured) | 120.8 | 118.7 | 116.9 | 115.2 | 112.7 | 108.8 | 103.7 | 99.1 | 117.5 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0076 | 0.0296 | 0.109 | 0.336 | 0.729 | 1.220 | 2.340 | 6.470 | |
| | $K_3$ | -3 | -1.1203 | 1.536 | 0.650 | -1.214 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.072 | 49.973 | 52.710 | 52.050 | 50.578 | 50.784 | 51.904 | 56.034 | |
| | $L_P$ (Predicted) | 72.727 | 68.726 | 64.189 | 63.149 | 62.121 | 58.015 | 51.795 | 43.065 | 66.2 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 63.3 | 61.7 | 59.9 | 57.7 | 54.7 | 52.1 | 47.7 | 43.1 | 60.2 |
| | $L_W$ (Measured) | 117.8 | 116.2 | 114.4 | 112.2 | 109.2 | 106.6 | 102.2 | 97.6 | 114.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0114 | 0.0444 | 0.1635 | 0.504 | 1.093 | 1.830 | 3.510 | 9.705 | |
| | $K_3$ | -3 | -1.011 | 1.837 | 0.862 | -1.186 | -1.5 | -1.5 | -1.5 | |
| | $K_4$ | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | |
| | DI - $\Sigma$ K | 52.076 | 54.097 | 57.065 | 56.431 | 54.971 | 55.394 | 57.074 | 63.269 | |
| | $L_P$ (Predicted) | 65.724 | 62.102 | 57.334 | 55.768 | 54.228 | 51.205 | 45.125 | 34.330 | 58.9 |

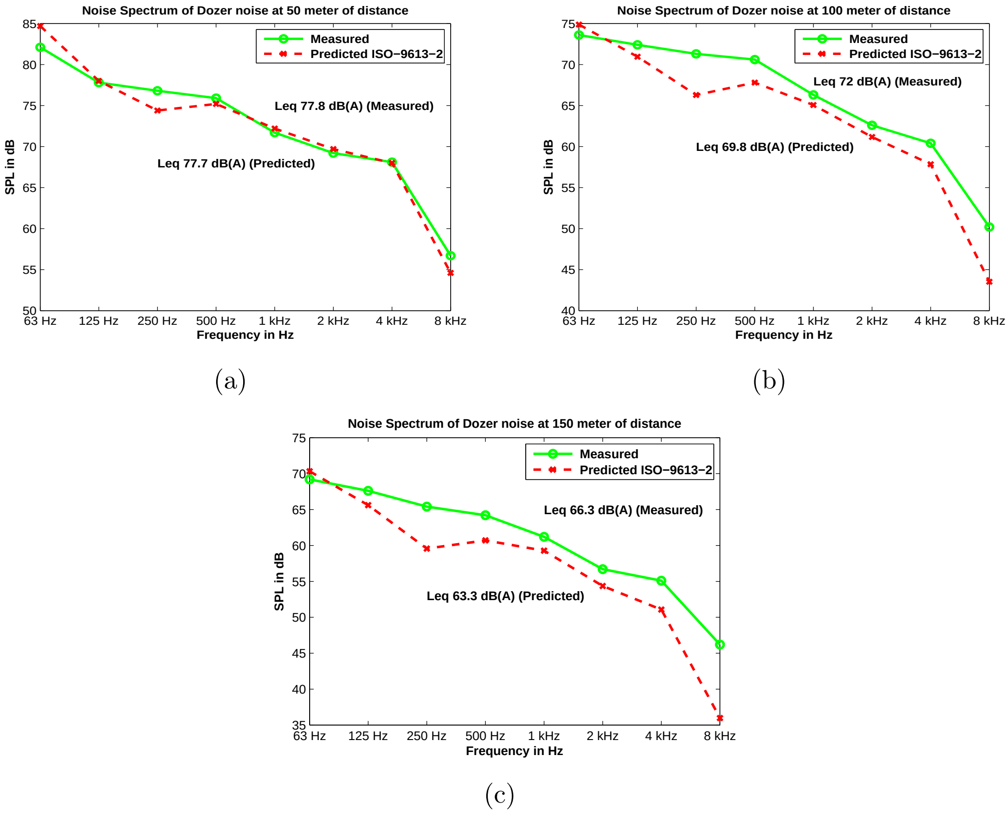



Figure 3.10: Spectrum analysis of Dozer noise at 50 m, 100 m and 150 m with ISO-9613-2

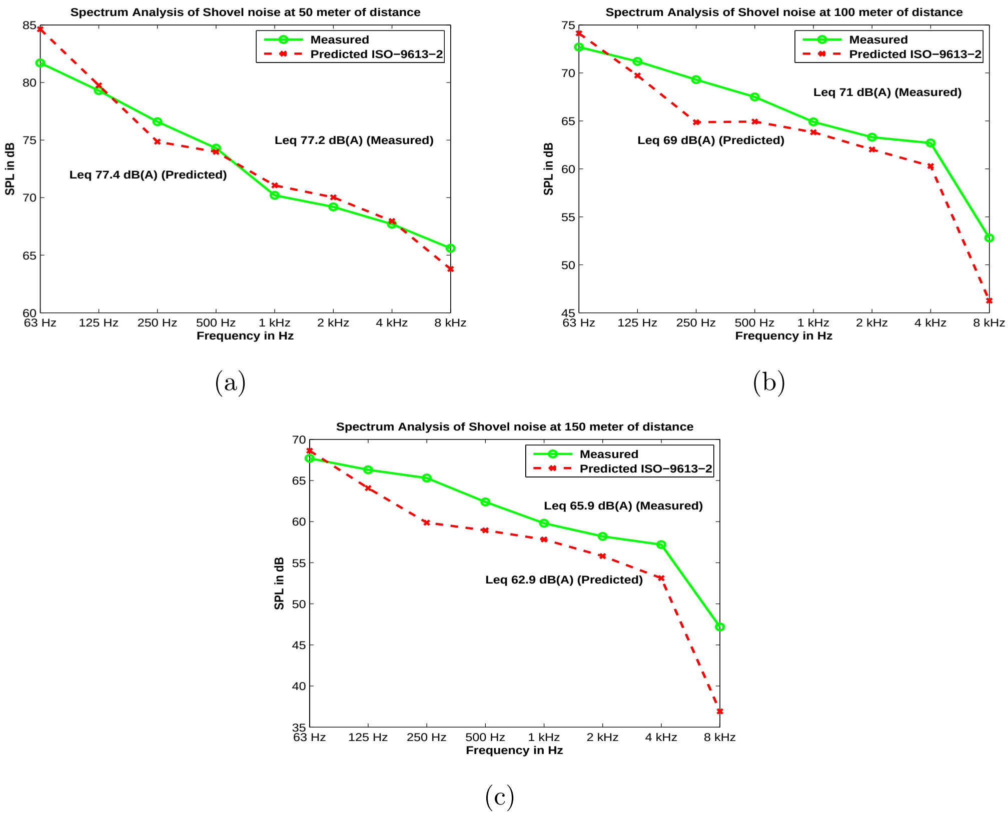
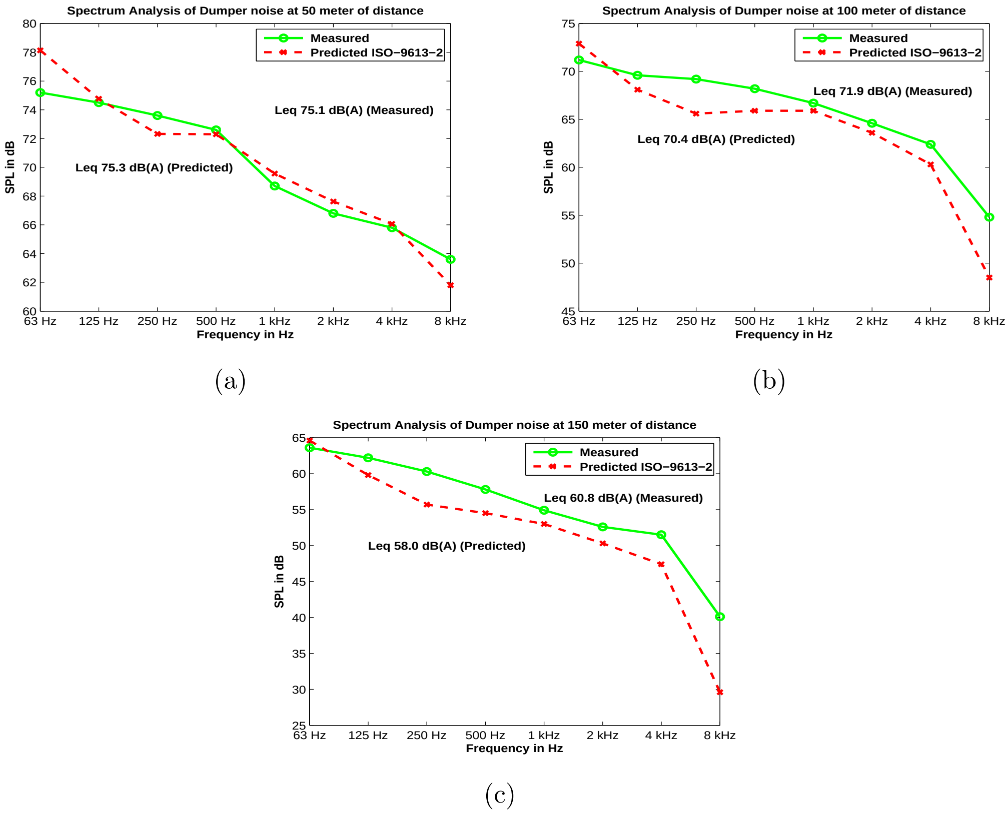
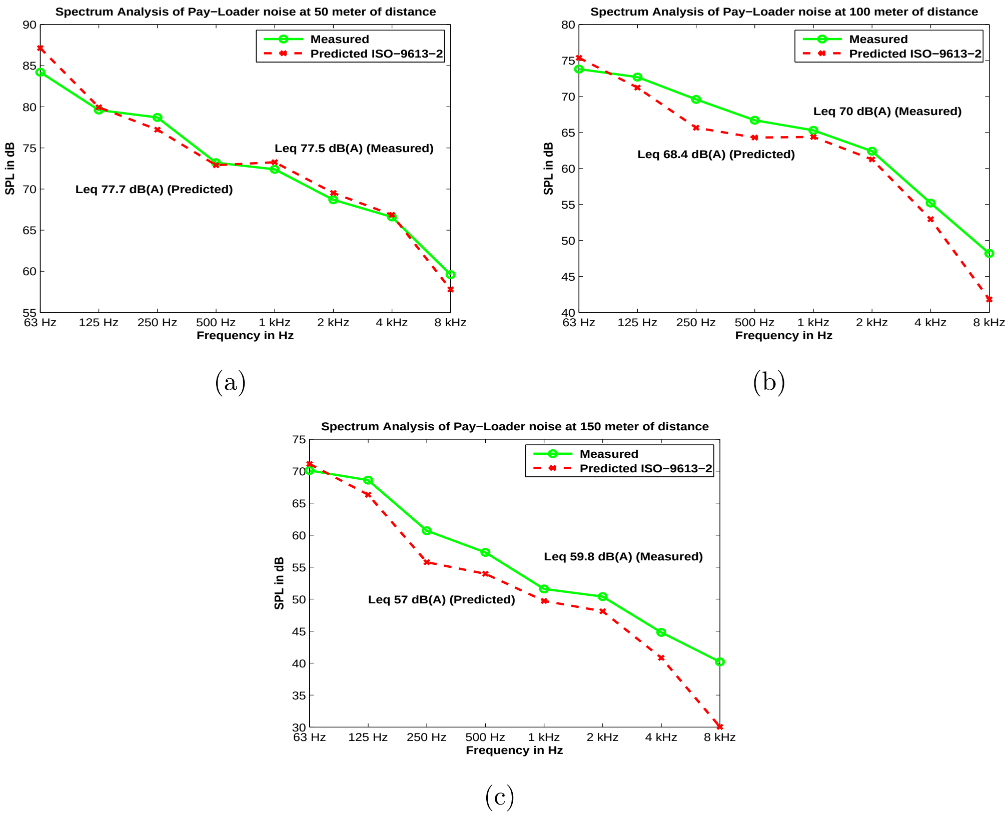



Figure 3.11: Spectrum analysis of Shovel noise at 50 m, 100 m and 150 m with ISO-9613-2



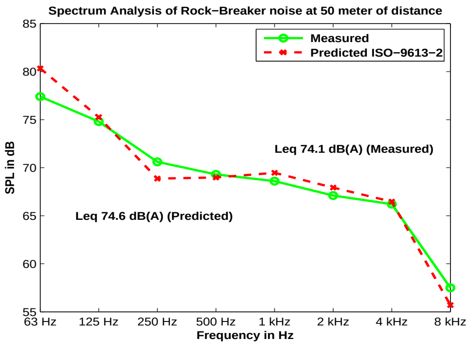

(a) (b) (c)

Figure 3.12: Spectrum analysis of Dumper noise at 50 m, 100 m and 150 m with ISO-9613-2

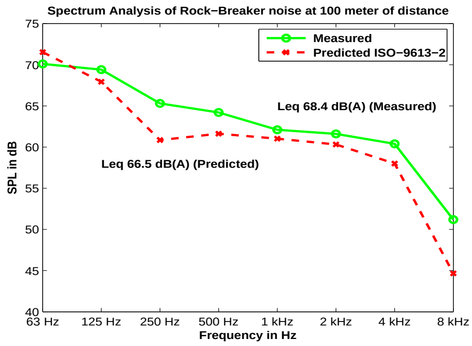



(a) (b) (c)

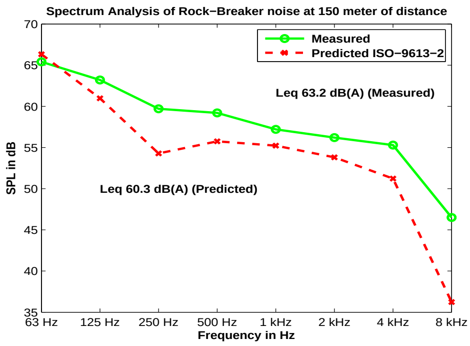
Figure 3.13: Spectrum analysis of Pay-Loader noise at 50 m, 100 m and 150 m with ISO-9613-2




(a)

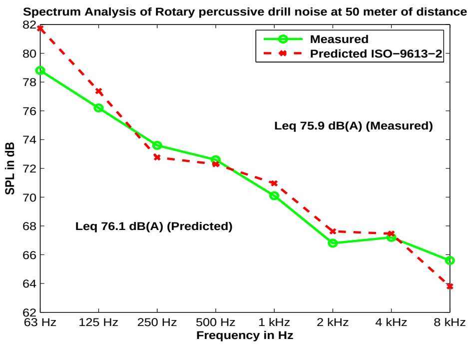



(b)

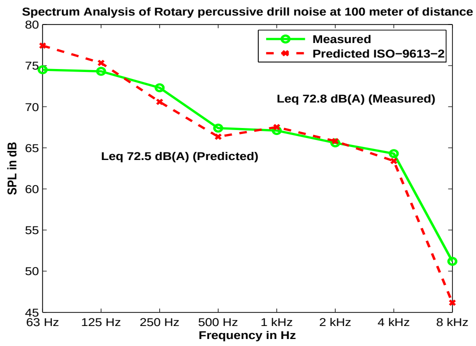



(c)

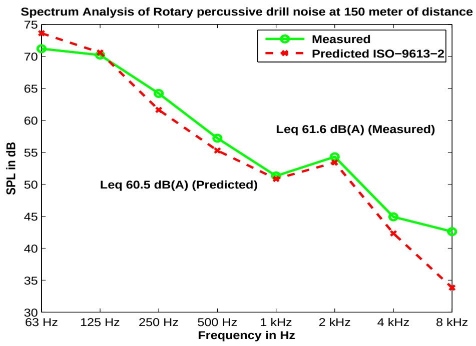
Figure 3.14: Spectrum Analysis of Rock-Breaker Noise at 50 m, 100 m and 150 m with ISO-9613-2




(a)

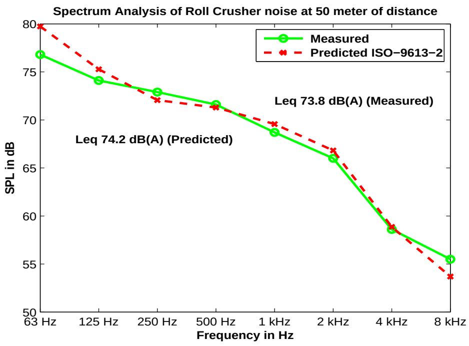



(b)

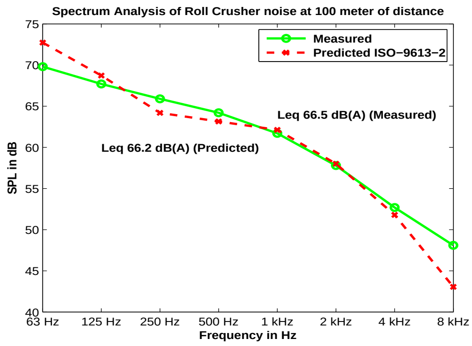



(c)

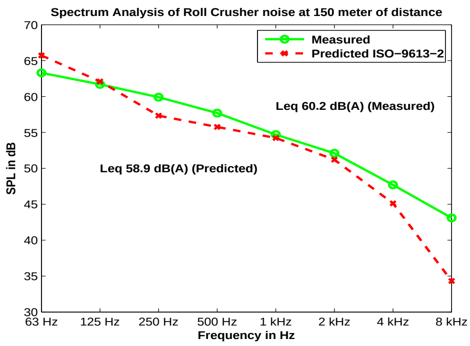
Figure 3.15: Spectrum analysis of Drill noise at 50 m, 100 m and 150 m with ISO-9613-2




(a)




(b)




(c)

Figure 3.16: Spectrum analysis of Crusher noise at 50 m, 100 m and 150 m with ISO-9613-2

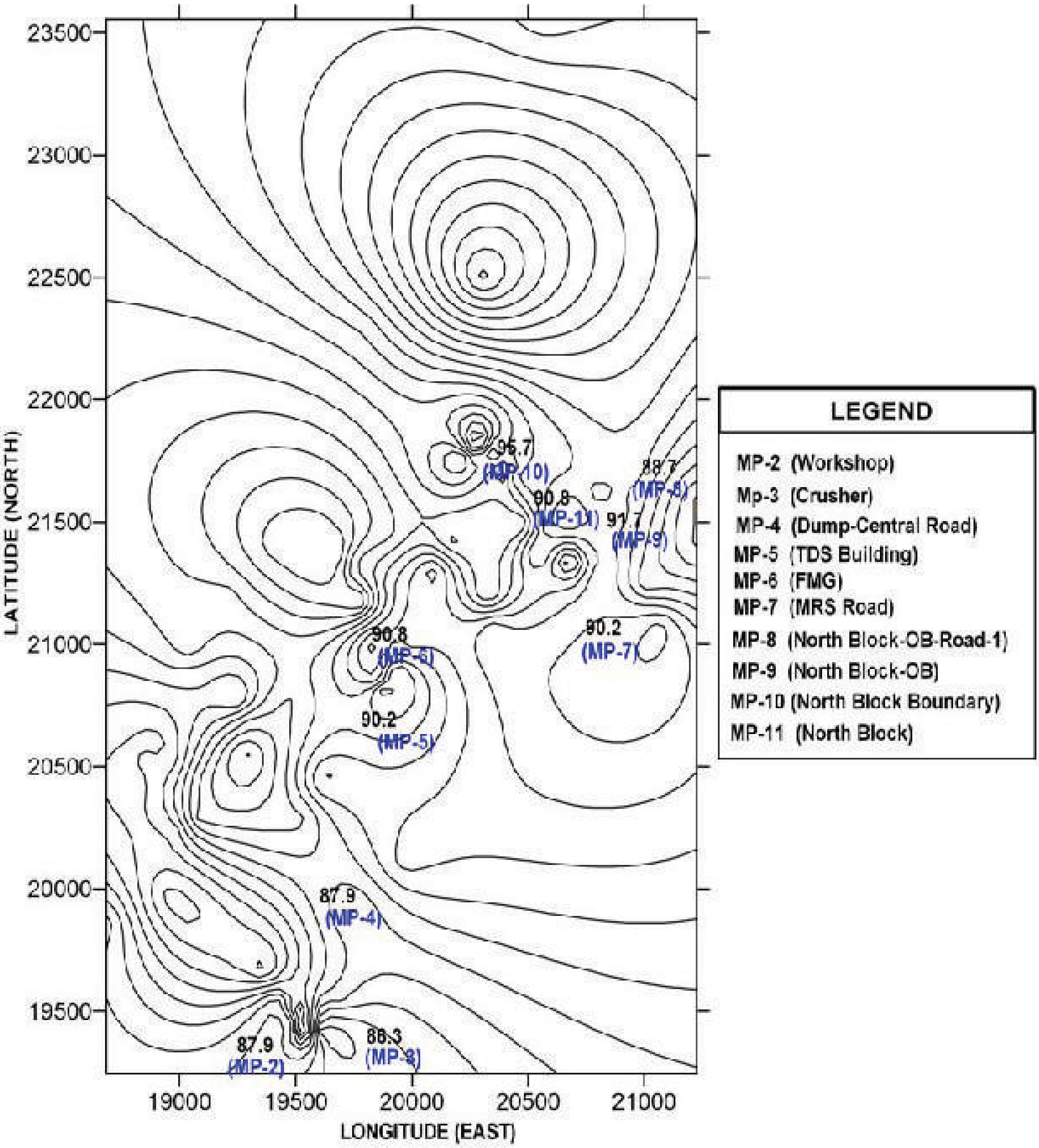



Figure 3.17: Contour plot of ISO-9613-2 noise prediction for Damonjodi bauxite mine, NALCO

### 3.4.2 Application of CONCAWE Noise Prediction Model

CONCAWE noise prediction model (Equation 3.4)is essentially empirical and was applied for predicting machineries noise in NALCO bauxite mine. The CONCAWE method is especially suited for assessments where prevailing winds and meteorological conditions do not fit normal conditions as in the other standards. CONCAWE is the only standard that allows the meteorological influence to be assessed. For this prediction model, all the calculations were made in the frequency ranges from 63 Hz to 4000 Hz. Attenuation factors $K_1$( Geometrical Divergence), $K_2$ (Atmospheric Absorption), $K_3$ (Ground Topography), $K_4$ (Meteorological Correction), $K_5$ (Source Height Effect). Attenuation due to barrier is taken as zero as there is no barrier present in the selected mine. All the attenuation factors are calculated as per the standard.As the formulas use third order polygons with large constants, their border value for the distance 0 m would be constant. Therefore the formulas are only valid for distances greater than 100 m. Hence, the value at the distance is set to zero and the value at 100 m is calculated using the formulas. Values between 0 and 100 m are calculated with linear interpolation. Table 3.14 to Table 3.20 represents the prediction results (CONCAWE) of all selected machineries with 50 m, 100 m and 150 m. Figure 3.18 to 3.24 represents sound spectrum analysis of all the selected machineries with CONCAWE prediction assessment. After getting the prediction results, contour plot was generated and represented in Fig. 3.25.

### 3.4.3 Application of ENM Noise Prediction Model

ENM model (Equation 3.20) was applied to predict noise in NALCO bauxite mine. The calculation procedure of ENM is quite similar to CONCAWE model in calculation of the attenuation due to absorption. For ENM model, all the calculations were made in the frequency ranges from 31.5 Hz to 8000 Hz. Attenuation factors $K_1$( Geometrical Divergence), $K_2$ (Atmospheric Absorption), $K_3$ (Ground Topography)and $K_4$ (Meteorological Correction). Attenuation due to barrier is taken as zero here. All the attenuation factors are calculated as per the standard. Table 3.21 to Table 3.27 represents the prediction result (ENM) of all selected machineries at 50 meter, 100 m and 150 m. Figure 3.26 to 3.32 represents sound spectrum analysis of all the selected machineries with ENM prediction result.Contour plot is generated using ENM prediction results and represented in Fig. 3.33.

Table 3.14: CONCAWE results for Dozer machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 82.1 | 77.8 | 76.8 | 75.9 | 71.7 | 69.2 | 68.1 | **77.8** |
| | $L_W$ (Measured) | 127 | 122.7 | 121.7 | 120.8 | 116.6 | 114.1 | 113 | **122.7** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 82 | 77.7 | 76.7 | 75.6 | 71.2 | 68.4 | 66.8 | **77.3** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 73.6 | 72.4 | 71.3 | 70.6 | 66.3 | 62.6 | 60.4 | **72** |
| | $L_W$ (Measured) | 124.6 | 123.4 | 122.3 | 121.6 | 117.3 | 113.6 | 111.4 | **123** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.84 | -0.048 | 5.2824 | 0.942 | 0 | -3.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | -0.086 | 0.482 | -1.697 | -4.761 | -2.266 | -1.724 | 0.287 | |
| | DI - $\Sigma$ K | 48.1382 | 47.7275 | 49.4096 | 51.8957 | 50.4907 | 50.6600 | 50.3020 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 76.4 | 75.6 | 72.9 | 69.7 | 66.8 | 62.9 | 61.0 | **72.3** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 69.2 | 67.6 | 65.4 | 64.2 | 61.2 | 56.7 | 55.1 | **66.2** |
| | $L_W$ (Measured) | 123.7 | 122.1 | 119.9 | 118.7 | 115.7 | 109.2 | 109.6 | **120.7** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0.053 | -0.741 | -3.427 | -5.580 | -3.240 | -2.078 | -0.390 | |
| | DI - $\Sigma$ K | 51.5397 | 52.1428 | 54.2347 | 56.1569 | 55.0859 | 55.0820 | 55.5286 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 72.1 | 69.9 | 65.6 | 62.5 | 60.6 | 56.1 | 54.0 | **65.6** |

Table 3.15: CONCAWE results for Shovel machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 81.7 | 79.3 | 76.6 | 74.3 | 70.2 | 69.2 | 67.7 | **77.0** |
| | $L_W$ (Measured) | 126.6 | 124.2 | 121.5 | 119.2 | 115.1 | 114.1 | 112.6 | **121.9** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 81.6 | 79.2 | 76.5 | 74.0 | 69.7 | 68.4 | 66.4 | **76.4** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 72.7 | 71.2 | 69.3 | 67.5 | 64.9 | 63.3 | 62.7 | **70.9** |
| | $L_W$ (Measured) | 123.7 | 122.2 | 120.3 | 118.5 | 115.9 | 114.3 | 113.7 | **121.9** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.282 | 0.942 | 0 | -3.500 | |
| | $K_4$ | 0.0004 | 0 | -1 | -1 | -0.859 | -1.035 | 0.017 | |
| | $K_5$ | -0.119 | 0 | -1.555 | -5.801 | -2.455 | -1.565 | 0 | |
| | DI - $\Sigma$ K | 48.1051 | 47.2446 | 48.5516 | 49.8557 | 49.4416 | 49.7842 | 50.0322 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 75.6 | 74.9 | 71.7 | 68.6 | 66.4 | 64.5 | 63.6 | **72.3** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 67.7 | 66.3 | 65.3 | 62.4 | 59.8 | 58.2 | 57.2 | **65.9** |
| | $L_W$ (Measured) | 122.2 | 120.8 | 119.8 | 116.9 | 114.3 | 112.7 | 111.7 | **120.4** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | -0.230 | -0.598 | -1.739 | -1.739 | -2.737 | -2.019 | -1.324 | |
| | $K_5$ | 0 | -0.417 | -2.549 | -4.810 | -1.750 | -0.964 | 0 | |
| | DI - $\Sigma$ K | 51.2557 | 51.8683 | 53.3734 | 55.1876 | 53.8386 | 54.1776 | 54.5948 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 70.9 | 68.9 | 66.4 | 61.7 | 60.4 | 58.5 | 57.1 | **66.2** |

Table 3.16: CONCAWE results for Dumper machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 75.2 | 74.5 | 73.6 | 72.6 | 68.7 | 66.8 | 65.8 | **74.9** |
| | $L_W$ (Measured) | 120.1 | 119.4 | 118.5 | 117.5 | 113.6 | 111.7 | 110.7 | **119.8** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 75.1 | 74.4 | 73.4 | 72.3 | 68.2 | 66.0 | 64.5 | **74.3** |
| 100m | $L_P$ (Measured) | 71.2 | 69.6 | 69.2 | 68.2 | 66.7 | 64.6 | 62.4 | **71.8** |
| | $L_W$ (Measured) | 122.2 | 120.6 | 120.2 | 119.2 | 117.7 | 115.6 | 113.4 | **122.8** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.282 | 0.942 | 0 | -3.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | -0.107 | 0 | -2.116 | -5.937 | -2.826 | -2.150 | 0 | |
| | DI - $\Sigma$ K | 48.1170 | 47.2446 | 48.9905 | 50.7200 | 49.9310 | 50.2341 | 50.0146 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 74.0 | 73.3 | 71.2 | 68.4 | 67.7 | 65.3 | 63.3 | **72.7** |
| 150m | $L_P$ (Measured) | 63.8 | 62.6 | 60.8 | 58.2 | 55.3 | 53.4 | 52.2 | **61.3** |
| | $L_W$ (Measured) | 118.3 | 117.1 | 115.3 | 112.7 | 109.8 | 107.9 | 106.7 | **115.8** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.030 | 0.135 | 0.465 | 1.125 | 1.980 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0.067 | -0.924 | -4.274 | -6.959 | -4.040 | -2.592 | -0.487 | |
| | DI - $\Sigma$ K | 51.4858 | 51.9597 | 53.3882 | 54.7787 | 54.2857 | 54.5687 | 55.4321 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 66.8 | 65.1 | 61.9 | 57.9 | 55.5 | 53.3 | 51.2 | **61.5** |

Table 3.17: CONCAWE results for Pay-Loader machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 84.2 | 79.6 | 78.7 | 73.2 | 72.4 | 68.7 | 66.6 | **77.4** |
| | $L_W$ (Measured) | 129.1 | 124.5 | 123.6 | 118.1 | 117.3 | 113.6 | 111.5 | **122.3** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 84.1 | 79.5 | 78.6 | 72.9 | 71.9 | 67.9 | 65.3 | **77.0** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 73.8 | 72.7 | 69.6 | 66.7 | 65.3 | 62.4 | 55.2 | **70.0** |
| | $L_W$ (Measured) | 124.8 | 123.7 | 120.6 | 117.7 | 116.3 | 113.4 | 106.2 | **121.0** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.282 | 0.942 | 0 | -3.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | -0.1 | 0 | -1.986 | -5.572 | -2.652 | -2.018 | 0 | |
| | DI - $\Sigma$ K | 48.1235 | 47.2446 | 49.1203 | 51.0841 | 50.1043 | 50.3660 | 50.0146 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 76.6 | 76.4 | 71.4 | 66.6 | 66.1 | 63.0 | 56.1 | **71.0** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 70.1 | 68.6 | 60.7 | 57.3 | 51.6 | 50.4 | 44.8 | **59.7** |
| | $L_W$ (Measured) | 124.6 | 123.1 | 115.2 | 111.8 | 106.1 | 104.9 | 99.3 | **114.2** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | -0.867 | -4.012 | -6.532 | -3.792 | -2.433 | -0.457 | |
| | DI - $\Sigma$ K | 51.4858 | 52.0164 | 53.6503 | 55.2055 | 54.5335 | 54.7276 | 55.4620 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 73.1 | 71.0 | 61.5 | 56.6 | 51.5 | 50.1 | 43.8 | **60.3** |

Table 3.18: CONCAWE results for Rock-Breaker machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 77.4 | 74.8 | 70.6 | 69.3 | 68.6 | 67.1 | 66.2 | **74.1** |
| | $L_W$ (Measured) | 122.3 | 119.7 | 115.5 | 114.2 | 113.5 | 112.0 | 111.1 | **119** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 77.3 | 74.7 | 70.5 | 69.0 | 68.1 | 66.3 | 64.9 | **73.5** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 70.1 | 69.4 | 65.3 | 64.2 | 62.1 | 61.6 | 60.4 | **66.3** |
| | $L_W$ (Measured) | 121.1 | 120.4 | 116.3 | 115.2 | 113.1 | 112.6 | 111.4 | **119.4** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.2824 | 0.9424 | 0 | -3.5 | |
| | $K_4$ | -0.372 | -0.489 | -0.534 | -0.542 | -0.404 | -2.556 | -1.069 | |
| | $K_5$ | 0 | 0 | -1.512 | -4.841 | -2.213 | -0.277 | 0 | |
| | DI - $\Sigma$ K | 47.8514 | 46.7554 | 49.0598 | 51.2727 | 50.1395 | 49.5508 | 48.9450 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 71.5 | 68.0 | 60.8 | 61.6 | 61.0 | 60.3 | 58.0 | **67.4** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 65.4 | 63.2 | 59.7 | 59.2 | 57.2 | 56.2 | 55.3 | **61.1** |
| | $L_W$ (Measured) | 119.9 | 117.7 | 114.2 | 113.7 | 111.7 | 110.7 | 109.8 | **115.6** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.6365 | 0.616 | -2.320 | |
| | $K_4$ | -1.452 | -1.508 | -1.985 | -2.033 | -2.539 | -3.713 | -3.035 | |
| | $K_5$ | 0 | 0 | -2.488 | -4.801 | -1.937 | 0 | 0 | |
| | DI - $\Sigma$ K | 50.0332 | 51.3757 | 53.1888 | 54.9032 | 53.8492 | 53.4475 | 52.8837 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1 | |
| | $L_P$ (Predicted) | 67.6 | 62.8 | 60.5 | 56.8 | 56.8 | 56.3 | 48.1 | **61.9** |

Table 3.19: CONCAWE results for Drill machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 78.8 | 76.2 | 73.6 | 72.6 | 70.1 | 66.8 | 67.2 | 75.6 |
| | $L_W$ (Measured) | 123.7 | 121.1 | 118.5 | 117.5 | 115.0 | 111.7 | 112.1 | 120.5 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 78.7 | 76.1 | 73.5 | 72.3 | 69.6 | 66.0 | 65.9 | 75.0 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 74.5 | 74.3 | 72.3 | 67.4 | 67.1 | 65.6 | 64.3 | 72.7 |
| | $L_W$ (Measured) | 125.5 | 125.3 | 123.3 | 118.4 | 118.1 | 116.6 | 115.3 | 123.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.282 | 0.942 | 0 | -3.5 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | -0.154 | 0 | -3.045 | -8.545 | -4.067 | -3.095 | 0 | |
| | DI - $\Sigma$ K | 48.0698 | 47.2446 | 48.0607 | 48.1112 | 48.6892 | 49.2892 | 50.0146 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 77.4 | 78.0 | 75.2 | 70.2 | 69.4 | 67.3 | 65.2 | 74.9 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 71.2 | 70.2 | 64.2 | 57.2 | 51.3 | 54.3 | 44.9 | **61.5** |
| | $L_W$ (Measured) | 125.7 | 124.7 | 118.7 | 111.7 | 105.8 | 108.8 | 99.4 | **116.0** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | -1.330 | -6.152 | -10.017 | -5.815 | -3.731 | -0.701 | |
| | DI - $\Sigma$ K | 51.4858 | 51.5536 | 51.5100 | 51.7208 | 52.5103 | 53.4296 | 55.2180 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 74.2 | 73.1 | 67.1 | 59.9 | 53.2 | 55.3 | 44.1 | **63.9** |

Table 3.20: CONCAWE results for Crusher machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 50m | $L_P$ (Measured) | 76.8 | 74.1 | 72.9 | 71.6 | 68.7 | 66.0 | 58.6 | **73.7** |
| | $L_W$ (Measured) | 121.7 | 119.0 | 117.8 | 116.5 | 113.6 | 110.9 | 103.5 | **118.6** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.005 | 0.01 | 0.045 | 0.155 | 0.375 | 0.66 | 1.225 | |
| | $K_3$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | $K_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 44.9696 | 44.9746 | 45.0096 | 45.1196 | 45.3396 | 45.6246 | 46.1896 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 76.7 | 74.0 | 72.8 | 71.3 | 68.2 | 65.2 | 57.3 | **73.3** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 100m | $L_P$ (Measured) | 69.8 | 67.7 | 65.9 | 64.2 | 61.7 | 57.8 | 52.7 | **63.2** |
| | $L_W$ (Measured) | 120.8 | 118.7 | 116.9 | 115.2 | 112.7 | 108.8 | 103.7 | **114.2** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | |
| | $K_3$ | -2.850 | -3.840 | -0.048 | 5.282 | 0.942 | 0 | -3.5 | |
| | $K_4$ | -0.372 | -0.489 | -0.534 | -0.542 | -0.404 | -2.556 | -1.069 | |
| | $K_5$ | 0 | 0 | -2.494 | -7.986 | -3.650 | -0.458 | 0 | |
| | DI - $\Sigma$ K | 47.8514 | 46.7554 | 48.0777 | 48.1284 | 48.7021 | 49.3705 | 48.9450 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 70.8 | 70.1 | 67.1 | 64.5 | 60.0 | 54.3 | 50.1 | **65.8** |

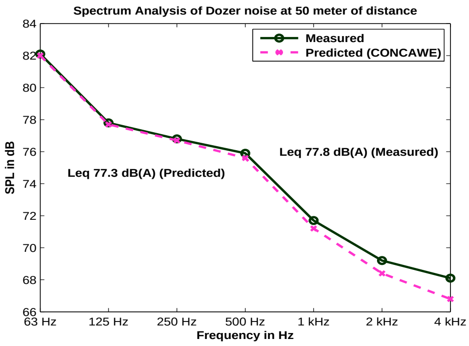
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|
| | | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | |
| 150m | $L_P$ (Measured) | 63.3 | 61.7 | 59.9 | 57.7 | 54.7 | 52.1 | 47.7 | **57.1** |
| | $L_W$ (Measured) | 117.8 | 116.2 | 114.4 | 112.2 | 109.2 | 106.6 | 102.2 | **111.6** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.015 | 0.03 | 0.135 | 0.465 | 1.125 | 1.98 | 3.675 | |
| | $K_3$ | -3.093 | -1.710 | 2.963 | 6.708 | 2.636 | 0.616 | -2.320 | |
| | $K_4$ | -1.452 | -1.508 | -1.985 | -2.033 | -2.539 | -3.713 | -3.035 | |
| | $K_5$ | 0 | 0 | -4.103 | -7.918 | -3.195 | 0 | 0 | |
| | DI - $\Sigma$ K | 50.0332 | 51.3757 | 51.5731 | 51.7855 | 52.5911 | 53.4475 | 52.8837 | |
| | A-Correction | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | |
| | $L_P$ (Predicted) | 66.1 | 63.0 | 60.6 | 57.4 | 54.0 | 48.7 | 44.7 | **59.3** |

Table 3.21: ENM results for Dozer machine

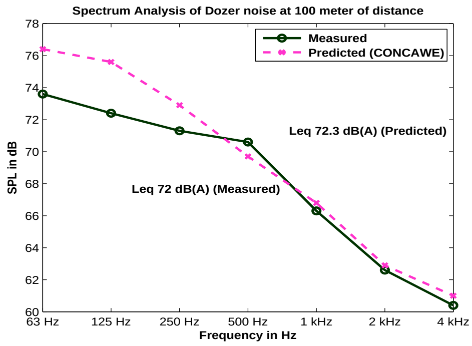
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 82.5 | 82.1 | 77.8 | 76.8 | 75.9 | 71.7 | 69.2 | 68.1 | 56.7 | 77.8 |
| | $L_W$ (Measured) | 127.4 | 127.0 | 122.7 | 121.7 | 120.8 | 116.6 | 114.1 | 113.0 | 101.6 | 122.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 85.4304 | 85.0304 | 80.7254 | 79.6904 | 78.6804 | 74.2604 | 71.4754 | 69.8104 | 56.4254 | 80.3 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 75.4 | 73.6 | 72.4 | 71.3 | 70.6 | 66.3 | 62.6 | 60.4 | 50.2 | 72.0 |
| | $L_W$ (Measured) | 126.4 | 124.6 | 123.4 | 122.3 | 121.6 | 117.3 | 113.6 | 111.4 | 101.2 | 123.0 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.01 | 0.01 | 0.02 | 0.09 | 0.31 | 0.75 | 1.32 | 2.45 | 6.42 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 78.3254 | 76.5254 | 75.3154 | 74.1454 | 73.2254 | 68.4854 | 64.2154 | 60.8854 | 46.7154 | 74.2 |

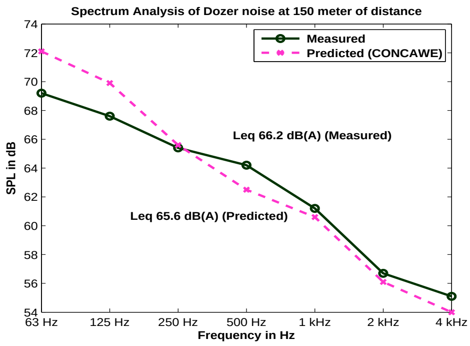
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 71.2 | 69.2 | 67.6 | 65.4 | 64.2 | 61.2 | 56.7 | 55.1 | 46.2 | 66.3 |
| | $L_W$ (Measured) | 125.7 | 123.7 | 122.1 | 119.9 | 118.7 | 115.7 | 111.2 | 109.6 | 100.7 | 120.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 49.3796 | 49.3796 | 50.4446 | 54.4996 | 49.4696 | 47.3696 | 51.2446 | 52.8396 | 58.7946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 76.3204 | 74.3204 | 71.6554 | 65.4004 | 69.2304 | 68.3304 | 59.9554 | 56.7604 | 41.9054 | 71.3 |




(a)

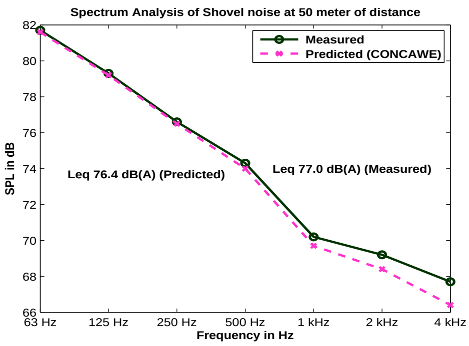



(b)

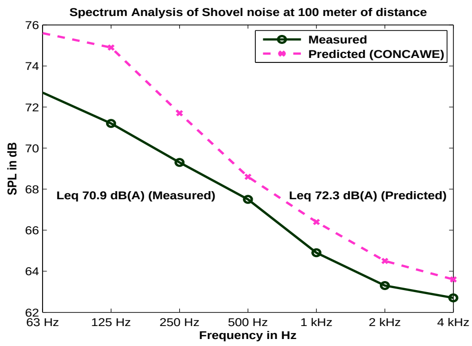



(c)

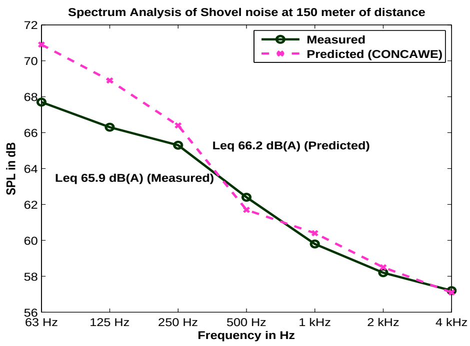
Figure 3.18: Spectrum analysis of Dozer noise at 50 m, 100 m and 150 m with CONCAWE




(a)

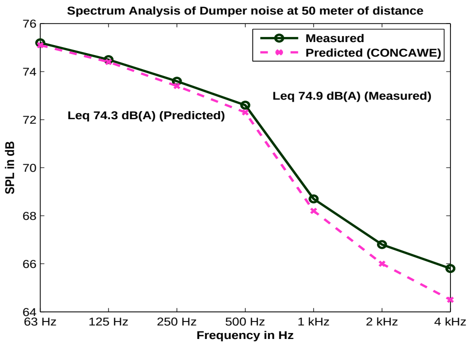



(b)

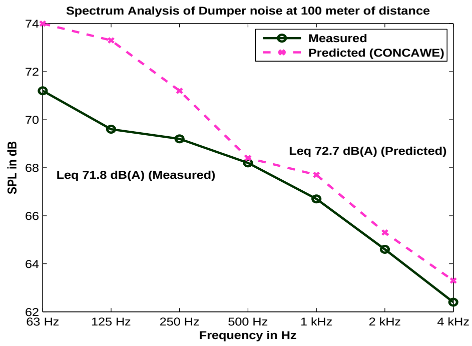



(c)

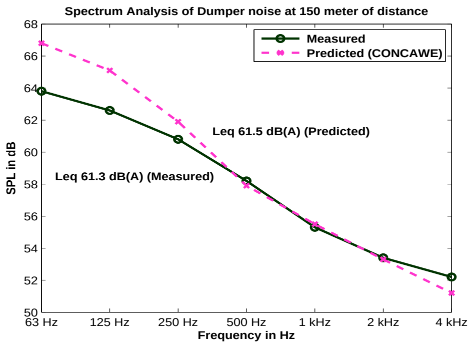
Figure 3.19: Spectrum analysis of Shovel noise at 50 m, 100 m and 150 m with CONCAWE




(a)

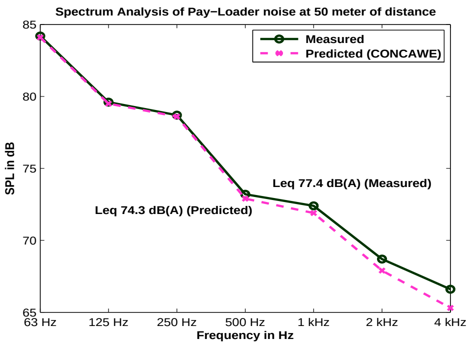



(b)

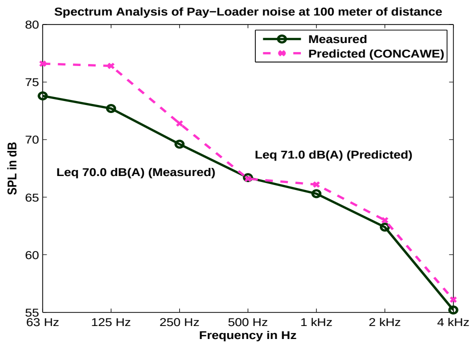



(c)

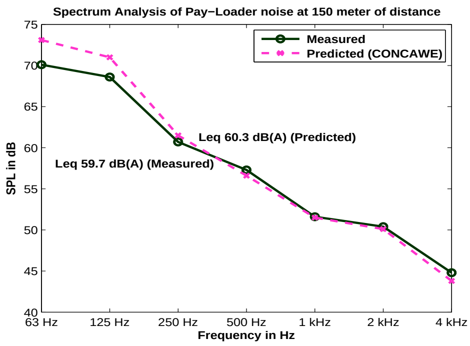
Figure 3.20: Spectrum analysis of Dumper noise at 50 m, 100 m and 150 m with CONCAWE




(a)

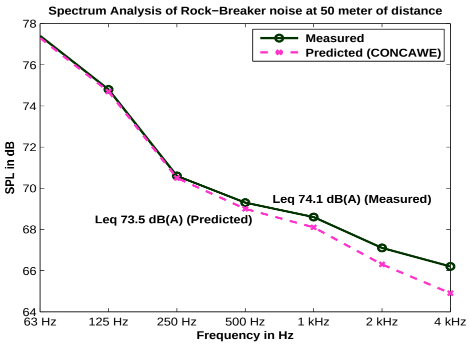



(b)

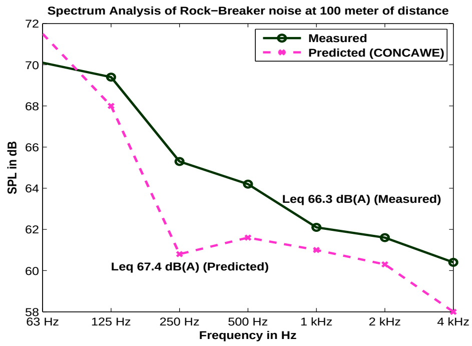



(c)

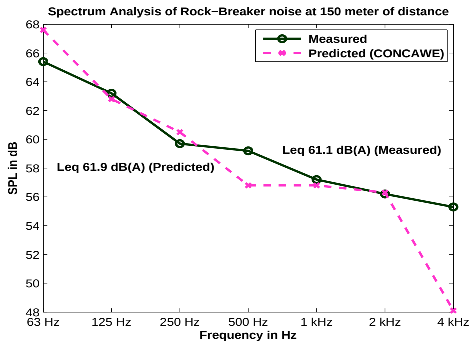
Figure 3.21: Spectrum analysis of Pay-Loader noise at 50 m, 100 m and 150 m with CONCAWE




(a)

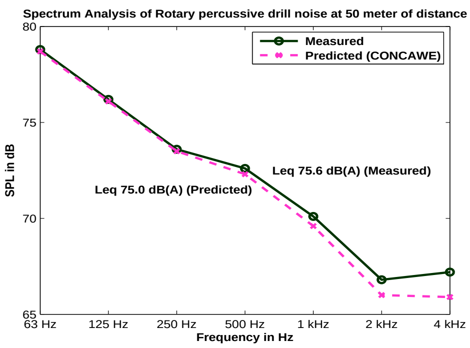



(b)

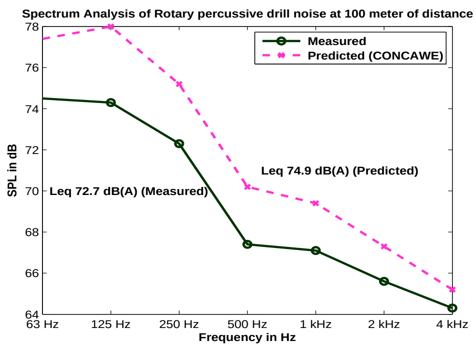



(c)

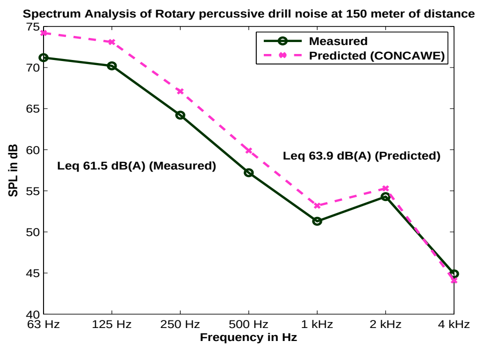
Figure 3.22: Spectrum analysis of Rock-Breaker noise at 50 m, 100 m and 150 m with CONCAWE




(a)

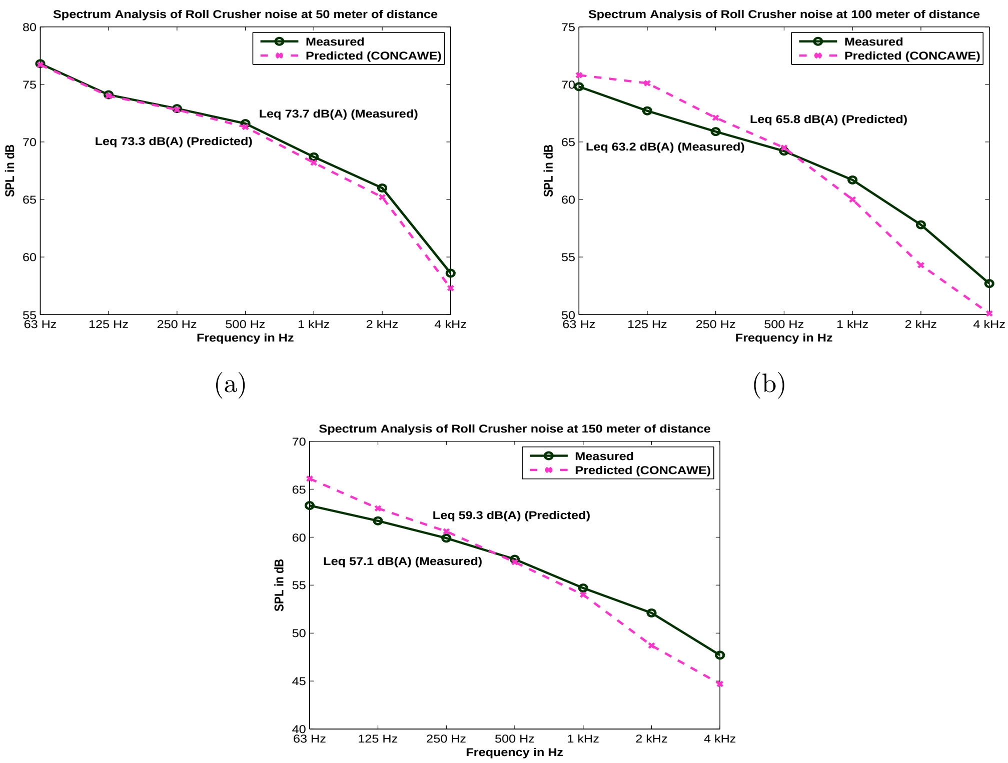



(b)




(c)

Figure 3.23: Spectrum analysis of Drill noise at 50 m, 100 m and 150 m with CONCAWE




(a) (b)

(c)

Figure 3.24: Spectrum analysis of Crusher noise at 50 m, 100 m and 150 m with CONCAWE

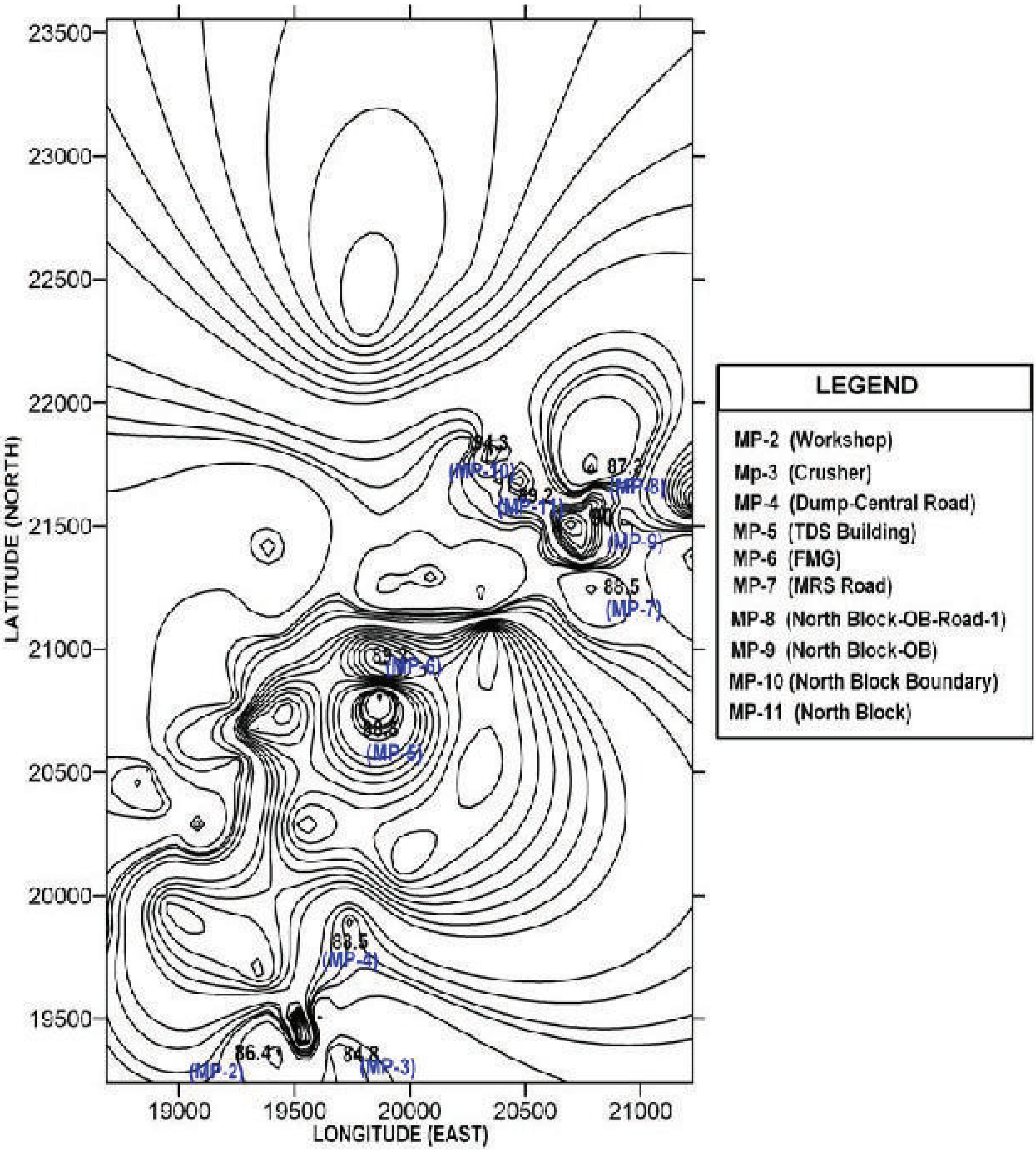



Figure 3.25: Contour plot of CONCAWE noise prediction for Damonjodi bauxite mine, NALCO

Table 3.22: ENM results for Shovel machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 82.4 | 81.7 | 79.3 | 76.6 | 74.3 | 70.2 | 69.2 | 67.7 | 65.6 | 77.2 |
| | $L_W$ (Measured) | 127.3 | 126.6 | 124.2 | 121.5 | 119.2 | 115.1 | 114.1 | 112.6 | 110.5 | 122.1 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 85.3304 | 84.6304 | 82.2254 | 79.4904 | 77.0804 | 72.7604 | 71.4754 | 69.4104 | 65.3254 | 79.6 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 74.3 | 72.7 | 71.2 | 69.3 | 67.5 | 64.9 | 63.3 | 62.7 | 52.8 | 71.0 |
| | $L_W$ (Measured) | 125.3 | 123.7 | 122.2 | 120.3 | 118.5 | 115.9 | 114.3 | 113.7 | 103.8 | 122.0 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 77.2254 | 75.6254 | 74.1154 | 72.1454 | 70.1254 | 67.0854 | 64.9154 | 63.1854 | 49.3154 | 72.9 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 69.8 | 67.7 | 66.3 | 65.3 | 62.4 | 59.8 | 58.2 | 57.2 | 47.2 | 65.9 |
| | $L_W$ (Measured) | 124.3 | 122.2 | 120.8 | 119.8 | 116.9 | 114.3 | 112.7 | 111.7 | 101.7 | 120.4 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 49.3796 | 49.3796 | 50.4446 | 54.4996 | 49.4696 | 47.3696 | 51.2446 | 52.8396 | 58.7946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 74.9204 | 72.8204 | 70.3554 | 65.3004 | 67.4304 | 66.9304 | 61.4554 | 58.8604 | 42.9054 | 70.4 |

Table 3.23: ENM results for Dumper machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 75.6 | 75.2 | 74.5 | 73.6 | 72.6 | 68.7 | 66.8 | 65.8 | 63.6 | 75.1 |
| | $L_W$ (Measured) | 120.5 | 120.1 | 119.4 | 118.5 | 117.5 | 113.6 | 111.7 | 110.7 | 108.5 | 120.0 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 78.5304 | 78.1304 | 77.4254 | 76.4904 | 75.3804 | 71.2604 | 69.0754 | 67.5104 | 63.3254 | 77.5 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 71.6 | 71.2 | 69.6 | 69.2 | 68.2 | 66.7 | 64.6 | 62.4 | 54.8 | 71.8 |
| | $L_W$ (Measured) | 122.6 | 122.2 | 120.6 | 120.2 | 119.2 | 117.7 | 115.6 | 113.4 | 105.8 | 122.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 74.5254 | 74.1254 | 72.5154 | 72.0454 | 70.8254 | 68.8854 | 66.2154 | 62.8854 | 51.3154 | 73.8 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 69.6 | 63.8 | 62.6 | 60.8 | 58.2 | 55.3 | 53.4 | 52.2 | 40.4 | 61.3 |
| | $L_W$ (Measured) | 124.1 | 118.3 | 117.1 | 115.3 | 112.7 | 109.8 | 107.9 | 106.7 | 94.9 | 115.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.3 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 49.3796 | 49.3796 | 50.4446 | 54.4996 | 49.4696 | 47.3696 | 51.2446 | 52.8396 | 58.7946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 74.7204 | 68.9204 | 66.6554 | 60.8004 | 63.2304 | 62.4304 | 56.6554 | 53.8604 | 36.1054 | 65.9 |

Table 3.24: ENM results for Payloader machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 83.2 | 84.2 | 79.6 | 78.7 | 73.2 | 72.4 | 68.7 | 66.6 | 59.6 | 77.5 |
| | $L_W$ (Measured) | 128.1 | 129.1 | 124.5 | 123.6 | 118.1 | 117.3 | 113.6 | 111.5 | 104.5 | 122.4 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 86.1304 | 87.1304 | 82.5254 | 81.5904 | 75.9804 | 74.9604 | 70.9754 | 68.3104 | 59.3254 | 80.0 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100 m | $L_P$ (Measured) | 75.5 | 73.8 | 72.7 | 69.6 | 66.7 | 65.3 | 62.4 | 55.2 | 48.2 | **70.0** |
| | $L_W$ (Measured) | 126.5 | 124.8 | 123.7 | 120.6 | 117.7 | 116.3 | 113.4 | 106.2 | 99.2 | **121.0** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1 | -1.1 | |
| | $L_P$ (Predicted) | 78.4254 | 76.7254 | 75.6154 | 72.4454 | 69.3254 | 67.4854 | 64.0154 | 55.6854 | 44.7154 | **72.2** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 71.3 | 70.1 | 68.6 | 60.7 | 57.3 | 51.6 | 50.4 | 44.8 | 40.2 | 59.8 |
| | $L_W$ (Measured) | 125.8 | 124.6 | 123.1 | 115.2 | 111.8 | 106.1 | 104.9 | 99.3 | 94.7 | 114.3 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 49.3796 | 49.3796 | 50.4446 | 54.4996 | 49.4696 | 47.3696 | 51.2446 | 52.8396 | 58.7946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1. | -1.1 | |
| | $L_P$ (Predicted) | 76.4204 | 75.2204 | 72.6554 | 60.7004 | 62.3304 | 58.7304 | 53.6554 | 46.4604 | 35.9054 | 64.1 |

Table 3.25: ENM results for Rock-Breaker machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 80.5 | 77.4 | 74.8 | 70.6 | 69.3 | 68.6 | 67.1 | 66.2 | 57.5 | 74.1 |
| | $L_W$ (Measured) | 125.4 | 122.3 | 119.7 | 115.5 | 114.2 | 113.5 | 112.0 | 111.1 | 102.4 | 119.0 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 83.4304 | 80.3304 | 77.7254 | 73.4904 | 72.0804 | 71.1604 | 69.3754 | 67.9104 | 57.2254 | 76.5 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 73.6 | 70.1 | 69.4 | 65.3 | 64.2 | 62.1 | 61.6 | 60.4 | 51.2 | 68.4 |
| | $L_W$ (Measured) | 124.6 | 121.1 | 120.4 | 116.3 | 115.2 | 113.1 | 112.6 | 111.4 | 102.2 | 119.4 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 76.5254 | 73.0254 | 72.3154 | 68.1454 | 66.8254 | 64.2854 | 63.2154 | 60.8854 | 47.7154 | 70.2 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 68.8 | 65.4 | 63.2 | 59.7 | 59.2 | 57.2 | 56.2 | 55.3 | 46.5 | 63.2 |
| | $L_W$ (Measured) | 123.3 | 119.9 | 117.7 | 114.2 | 113.7 | 111.7 | 110.7 | 109.8 | 101.0 | 117.7 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 51.5796 | 51.5796 | 51.5946 | 51.6996 | 52.0296 | 52.6896 | 53.5446 | 55.2396 | 61.1946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 71.7204 | 68.3204 | 66.1054 | 62.5004 | 61.6704 | 59.0104 | 57.1554 | 54.5604 | 39.8054 | 64.6 |

Table 3.26: ENM results for Drill machine

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 80.2 | 78.8 | 76.2 | 73.6 | 72.6 | 70.1 | 66.8 | 67.2 | 65.6 | 75.9 |
| | $L_W$ (Measured) | 125.1 | 123.7 | 121.1 | 118.5 | 117.5 | 115.0 | 111.7 | 112.1 | 110.5 | 120.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1 | -1.1 | |
| | $L_P$ (Predicted) | 83.1304 | 81.7304 | 79.1254 | 76.4904 | 75.3804 | 72.6604 | 69.0754 | 68.9104 | 65.3254 | 78.2 |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 74.7 | 74.5 | 74.3 | 72.3 | 67.4 | 67.1 | 65.6 | 64.3 | 51.2 | 72.8 |
| | $L_W$ (Measured) | 125.7 | 125.5 | 125.3 | 123.3 | 118.4 | 118.1 | 116.6 | 115.3 | 102.2 | 123.8 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 77.6254 | 77.4254 | 77.2154 | 75.1454 | 70.0254 | 69.2854 | 67.2154 | 64.7854 | 47.7154 | 74.7 |

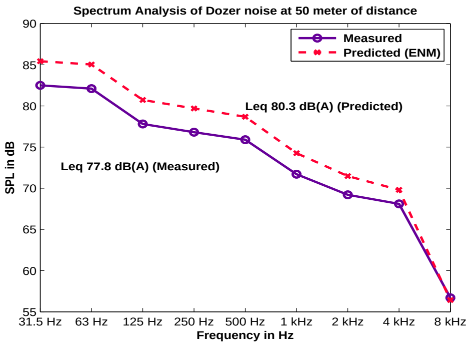
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 72.7 | 71.2 | 70.2 | 64.2 | 57.2 | 51.3 | 54.3 | 44.9 | 42.6 | 61.6 |
| | $L_W$ (Measured) | 127.2 | 125.7 | 124.7 | 118.7 | 111.7 | 105.8 | 108.8 | 99.4 | 97.1 | 116.1 |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 49.3796 | 49.3796 | 50.4446 | 54.4996 | 49.4696 | 47.3696 | 51.2446 | 52.8396 | 58.7946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1 | -1.1 | |
| | $L_P$ (Predicted) | 77.8204 | 76.3204 | 74.2554 | 64.2004 | 62.2304 | 58.4304 | 57.5554 | 46.5604 | 38.3054 | 65.3 |

Table 3.27: ENM results for Crusher machine

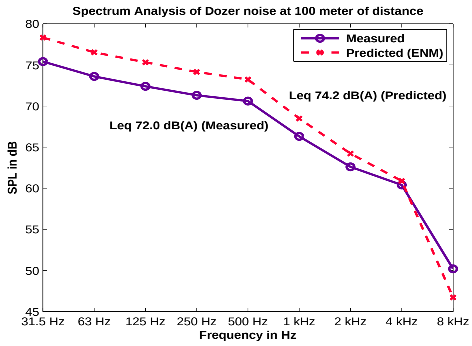
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 50m | $L_P$ (Measured) | 83.7 | 76.8 | 74.1 | 72.9 | 71.6 | 68.7 | 66.0 | 58.6 | 55.5 | **73.8** |
| | $L_W$ (Measured) | 128.6 | 121.7 | 119.0 | 117.8 | 116.5 | 113.6 | 110.9 | 103.5 | 100.4 | **118.7** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | 44.9 | |
| | $K_2$ | 0.0050 | 0.0050 | 0.0100 | 0.0450 | 0.1550 | 0.3750 | 0.6600 | 1.2250 | 3.2100 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 41.9696 | 41.9696 | 41.9746 | 42.0096 | 42.1196 | 42.3396 | 42.6246 | 43.1896 | 45.1746 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1 | -1.1 | |
| | $L_P$ (Predicted) | 86.6304 | 79.7304 | 77.0254 | 75.7904 | 74.3804 | 71.2604 | 68.2754 | 60.3104 | 55.2254 | **76.4** |

| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 100m | $L_P$ (Measured) | 74.9 | 69.8 | 67.7 | 65.9 | 64.2 | 61.7 | 57.8 | 52.7 | 48.1 | **66.5** |
| | $L_W$ (Measured) | 125.9 | 120.8 | 118.7 | 116.9 | 115.2 | 112.7 | 108.8 | 103.7 | 99.1 | **117.5** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | |
| | $K_2$ | 0.0100 | 0.0100 | 0.0200 | 0.0900 | 0.3100 | 0.7500 | 1.3200 | 2.4500 | 6.4200 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | DI - $\Sigma$ K | 48.0746 | 48.0746 | 48.0846 | 48.1546 | 48.3746 | 48.8146 | 49.3846 | 50.5146 | 54.4846 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 77.8254 | 72.7254 | 70.6154 | 68.7454 | 66.8254 | 63.8854 | 59.4154 | 53.1854 | 44.6154 | **68.7** |

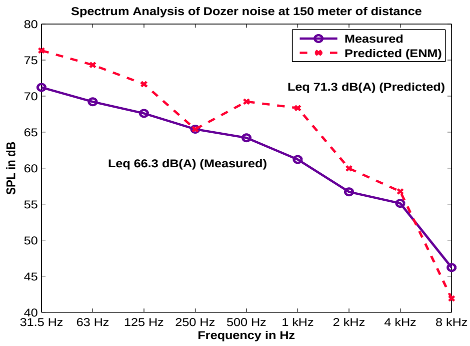
| Distance (in meter) | Parameters | 1/1 Octave band Frequency in Hz | | | | | | | | | Total (SPL) in dB (A) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 31.5 | 63 | 125 | 250 | 500 | 1000 | 2000 | 4000 | 8000 | |
| 150m | $L_P$ (Measured) | 67.7 | 63.3 | 61.7 | 59.9 | 57.7 | 54.7 | 52.1 | 47.7 | 43.1 | **60.2** |
| | $L_W$ (Measured) | 122.2 | 117.8 | 116.2 | 114.4 | 112.2 | 109.2 | 106.6 | 102.2 | 97.6 | **114.7** |
| | DI | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | 0.0646 | |
| | $K_1$ | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | 54.5 | |
| | $K_2$ | 0.0150 | 0.0150 | 0.0300 | 0.1350 | 0.4650 | 1.1250 | 1.9800 | 3.6750 | 9.6300 | |
| | $K_3$ | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | |
| | $K_4$ | -2.2 | -2.2 | -1.15 | 2.8 | -2.56 | -5.32 | -2.3 | -2.4 | -2.4 | |
| | DI - $\Sigma$ K | 51.5796 | 51.5796 | 51.5946 | 51.6996 | 52.0296 | 52.6896 | 53.5446 | 55.2396 | 61.1946 | |
| | A-Correction | -39.4 | -26.2 | -16.1 | -8.6 | -3.2 | 0.0 | 1.2 | 1.0 | -1.1 | |
| | $L_P$ (Predicted) | 70.6204 | 66.2204 | 64.6054 | 62.7004 | 60.1704 | 56.5104 | 53.0554 | 46.9604 | 36.4054 | **62.0** |




(a)

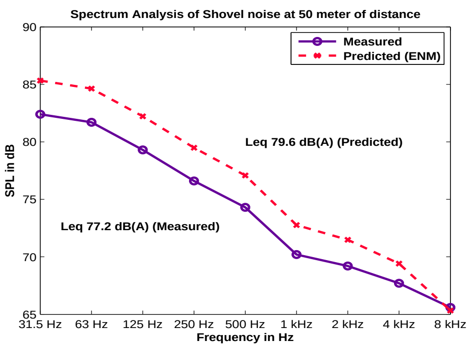



(b)

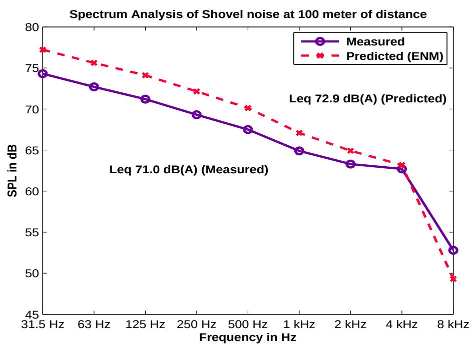



(c)

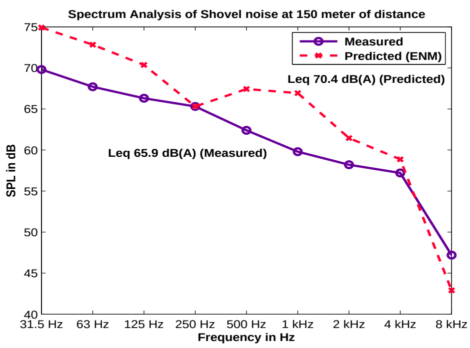
Figure 3.26: Spectrum Analysis of Dozer Noise at 50 m, 100 m and 150 m with ENM




(a)

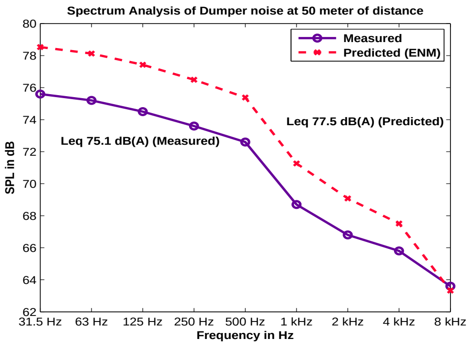



(b)

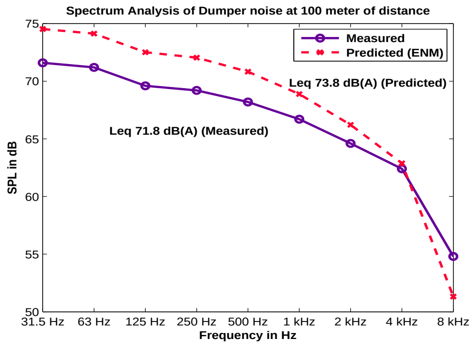



(c)

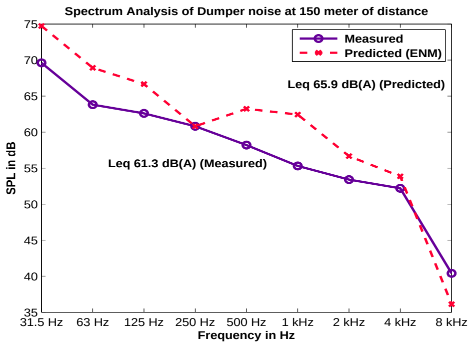
Figure 3.27: Spectrum analysis of Shovel noise at 50 m, 100 m and 150 m with ENM




(a)

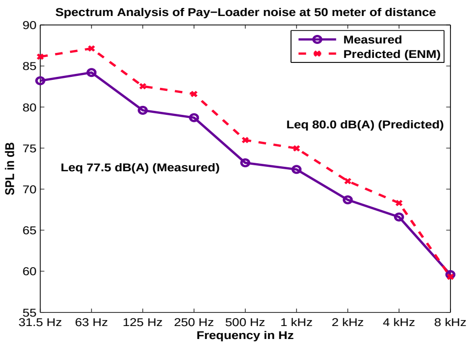



(b)

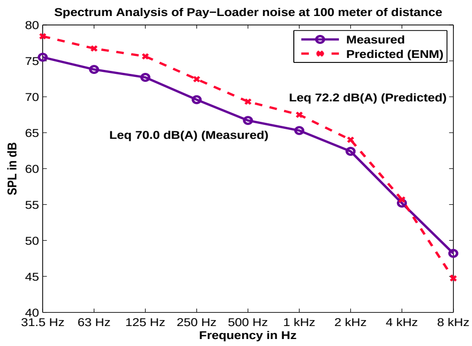



(c)

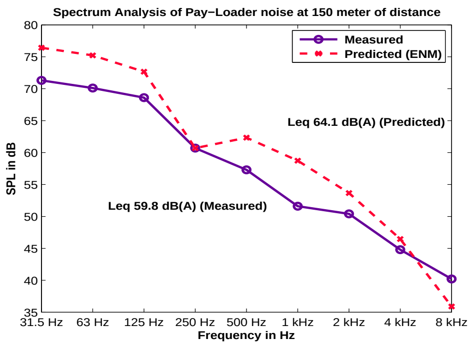
Figure 3.28: Spectrum analysis of Dumper noise at 50 m, 100 m and 150 m with ENM




(a)

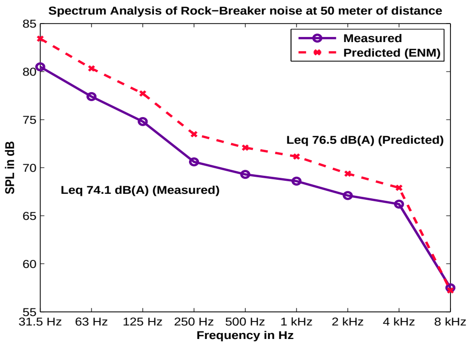



(b)

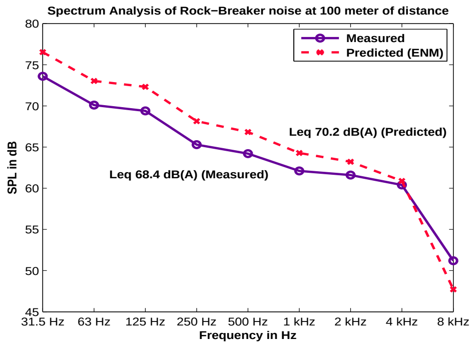



(c)

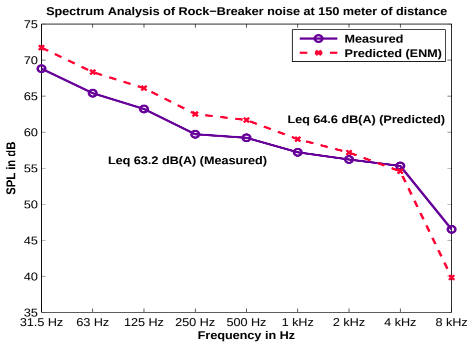
Figure 3.29: Spectrum analysis of Pay-Loader noise at 50 m, 100 m and 150 m with ENM




(a)

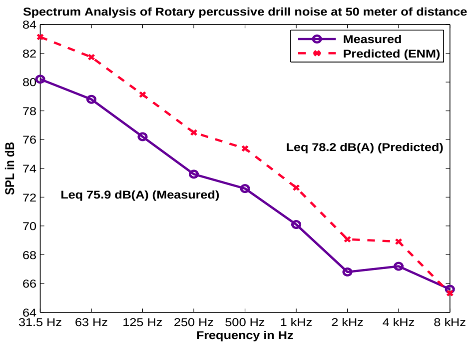



(b)

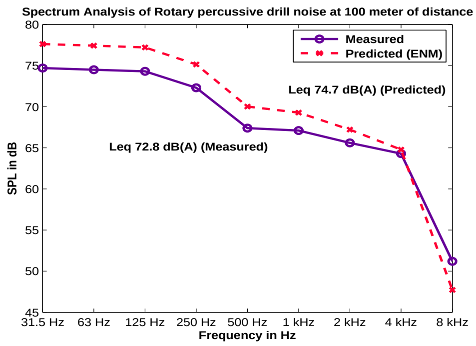



(c)

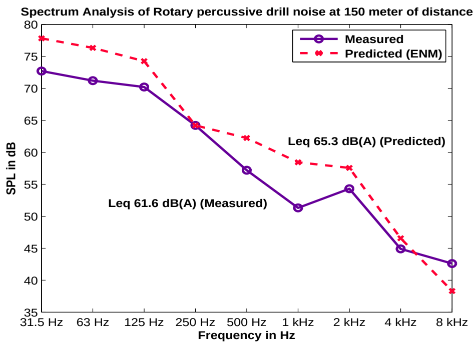
Figure 3.30: Spectrum Analysis of Rock-Breaker Noise at 50 m, 100 m and 150 m with ENM




(a)

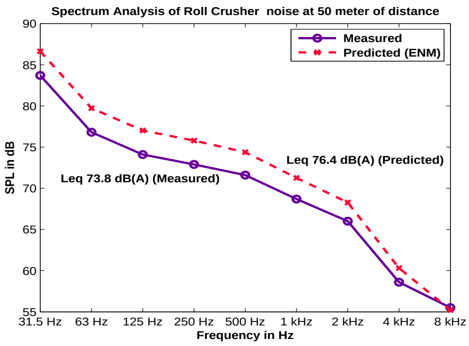



(b)

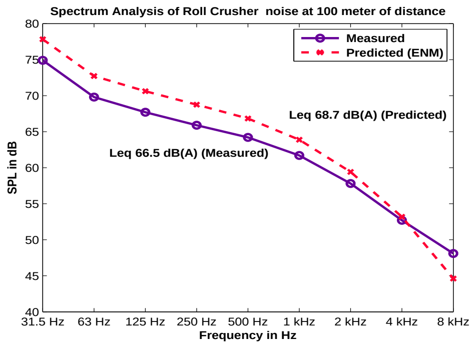



(c)

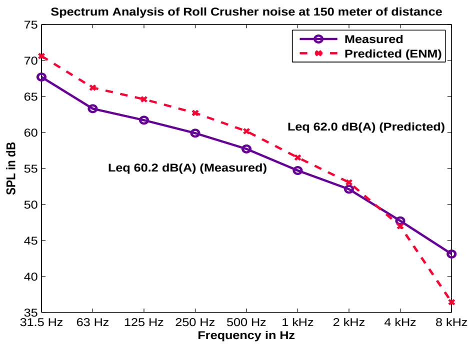
Figure 3.31: Spectrum analysis of Drill noise at 50 m, 100 m and 150 m with ENM




(a)




(b)




(c)

Figure 3.32: Spectrum analysis of Crusher noise at 50 m, 100 m and 150 m with ENM

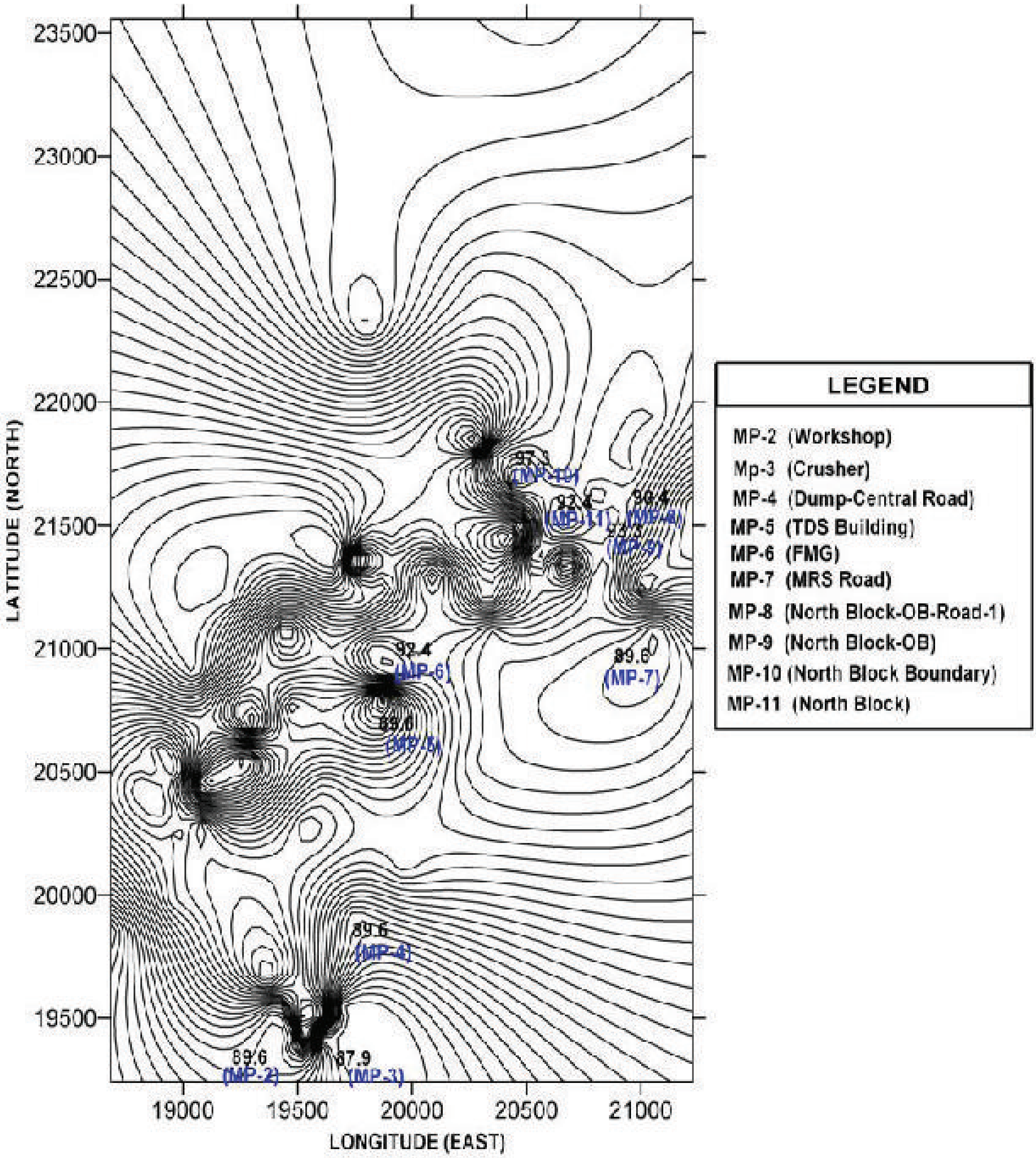



Figure 3.33: Contour plot of ENM noise prediction for Damonjodi bauxite mine,NALCO

## 3.5 Conclusion

Noise surveys of different machineries of different opencast mines were conducted. From the survey, it was concluded that shovel and drill produces noise levels exceeding the permissible level (90 dB(A)) in NALCO Damanjodi bauxite mine,where shovel, dumper and grader produces noise levels exceeding the permissible level (90 dB(A)) in Talcher, Balram opencast mine. All types of noise prediction models (both frequency and non frequency based noise prediction models) were used to predict appropriate noise status of the selected machineries with calculating all attenuation factors. Both the frequency and non-frequency based noise prediction models had given appropriate prediction results with intervals of distance from the source. At each interval of distance, sound pressure level of machineries was predicted by calculating all attenuation factors. This type of studies helped mining engineers to adopt administrative noise control strategies at work place. However, it was observed that noise prediction models are mathematically complex; took more CPU time to get result and all the calculations were repeated with every new data set. Hence intelligent system viz. fuzzy, neural network, radial basis function etc. based applications were required for developing intelligent noise prediction models. Noise contours were plotted for an opencast mine and it could be useful for noise zoning and mapping to minimize workers exposure as per statutory prescribed limits.

In ISO-9613-2, frequency band of 63 Hz - 8 kHz was used. From the model result, it was seen that for all the machineries, ISO-9613-2 model gave an overestimate value up to 50 m, whereas an underestimate result at 100 m and 150 m. For CONCAWE model, frequency band of 63 Hz-4 kHz was used and was found that CONCAWE model provided an underestimate value for all the selected machineries. For ENM model, frequency band of 31.5 Hz-8 kHz was used and provided an underestimate result for all the selected machineries.

Out of different models, it was observed that only ISO-9613-2 gave marginally overestimate results, whereas other models (ENM and CONCAWE) provided slightly underestimate value. Since all the methods except ISO-9613-2 were showing under estimate values beyond 50 m distance with marginal error, selectively models can be used for noise prediction based on the topographical and mining conditions.

# CHAPTER 4

# INTRODUCTION TO SOFT-COMPUTING TECHNIQUES

## 4.1 Introduction

Soft computing is considered as an emerging approach to computing, which parallels the remarkable ability of human mind to reason and learn in a circumstance of uncertainty and imprecision. The pioneer of soft computing, Lotfi A. Zadeh [142], has pointed hat, the guiding principle of soft computing was to exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, better rapport with reality. In contrast with hard computing methods that only deal with precision, certainty, and rigor, soft computing is effective in acquiring imprecise or sub-optimal but economical and competitive solutions. It takes advantage of intuition, which implies the human mind-based intuitive and subjective thinking. The motivation of applying the human intuition is that a large number of real-world problems cannot be solved by hard computing methods, due to the fact either they are too complex to handle or they cannot be described or catalogued by any analytical and exact models. However, in most cases, human experts are marvelously successful in dealing with these problems, e.g., face recognition in a noisy background. Zadeh also emphasizes precise measurement and control approaches are not always effective in coping with such difficult problems, but perception can often help. Therefore, the goal of soft computing is to exploit the imprecision and uncertainty in human decision making procedure, and achieve simple, reliable and low-cost solutions. Because of the aforementioned unique features, soft computing has drawn increasing research attention from people in different communities [143].

In general, soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. In effect, the role model for soft computing is the human mind. The principal constituents of soft computing (SC) are: Fuzzy Logic (FL), Neural Computing (NC), Evolutionary Computation (EC), Machine Learning (ML) and Probabilistic Reasoning (PR). That is, it is evolving the above relevant techniques together with the important advances in other new computing methods, such as artificial immune systems, common-sense reasoning, probabilistic reasoning, intelligent agents and chaos theory. The principal constituent methodologies in soft computing are complementary rather than competitive. Furthermore, soft computing may be viewed as a foundation component for the emerging field of conceptual intelligence [144].

Associated of the symbiotic relationship between FL, NC, EC and PR is the growing visibility of information/ intelligent systems which employ the constituent methodologies of soft computing in combination rather than separation. Table 4.1 lists three methodologies (FL, NC, EC) and their advantages. More specifically, it is advantageous to utilize artificial neural networks, fuzzy systems, and evolutionary algorithms in combination instead of isolation absolutely. A typical example to support this argument is the popular Neuro-Fuzzy or Adaptive Network Based Fuzzy Inference System (ANFIS) network model, which takes advantage of the capabilities of both fuzzy logic and neural networks. The Neuro-Fuzzy or ANFIS network is usually constructed to merge the fuzzy inference mechanism and neural networks into an integrated structure so that their individual weaknesses are overcome. The neuro-fuzzy technique can have the same topology with the feedforward neural network, i.e., nodes and layers. On the other hand, the input and output node functions inside are replaced with fuzzy membership functions. Regular back-propagation learning algorithm is applied to train the parameters of these fuzzy membership functions. It has been deployed in such many prospects as image processing and speech recognition [145]. .

Table 4.1: Soft Computing Constituents [145]

| Methodology | Advantage |
|---|---|
| Artificial Neural Network | Learning and Approximation |
| Fuzzy systems | Approximate reasoning |
| Evolutionary algorithms | Systematic random search |

The primary contribution of Soft Computing is the machinery of probability theory and the subsidiary techniques for decision-making under uncertainty, belief networks, cluster analysis and analysis of stochastic systems. During the past decades, the application of soft computing has covered a variety of areas. Besides control and instrumentation, other important fields include speech recognition, signal processing, telecommunications, power electronics systems, and system diagnosis. Soft computing has, in fact, shown a superior performance to the hard computing-based solutions in manipulating these real-world problems. With the rapid development of hardware platforms, e.g., digital signal processing (DSP) and neural networks/fuzzy logic chips, it is becoming more and more feasible to apply soft computing methods into practice[146, 147].

## 4.2 Fuzzy logic System

The fuzzy inference system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy-if-then rules and fuzzy reasoning. It has found successful applications in a wide variety of fields, such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition[148–153]. Because of its multidisciplinary nature, the fuzzy inference system is known by numerous other names, such as fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associate memory, fuzzy controller and simply fuzzy system.

Fuzzy expert system based on fuzzy set theory was introduced in 1965 by Lofti Zadeh [142] as a new way to represent vagueness in everyday life. It is a truth that most of the world's understanding is uncertain and unfocussed; hence, all the real system intrinsically contains incomplete and imprecise information. In order to be in agreement with the real system, the fuzzy systems work on the concept of vagueness through a set of rules called the rule base. The detailed analysis of fuzzy systems are widely available in technical literature [142, 144, 154–162].The main structure of a fuzzy rule based system is the fuzzy algorithm the fundamental concepts of which are derived from fuzzy logic. The generalized structure of a fuzzy system is presented in Fig.4.1. Fuzzy system comprises of four blocks viz: fuzzifier, knowledge base, inference engine and defuzzifier [142, 154].

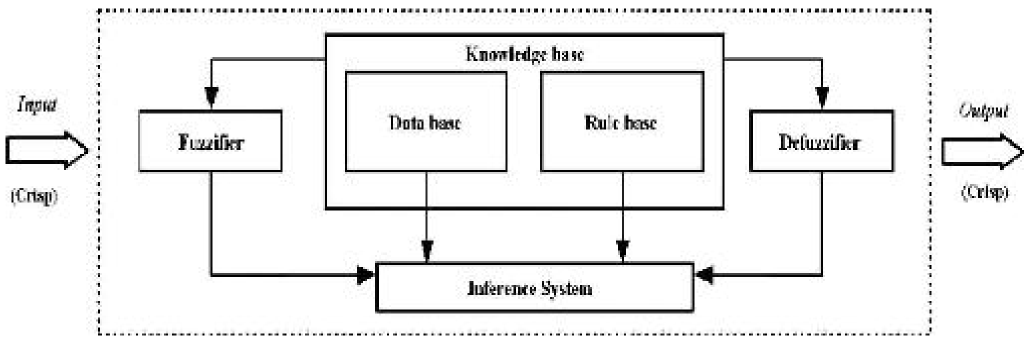



Figure 4.1: Structure of fuzzy rule based system.

### 4.2.1 Fuzzifier

The real world input to the fuzzy system is applied to the fuzzzifier. In fuzzy literature, this input is called crisp input since it contains precise information the parameter.

The fuzzifier converts this precise quantity to the form of imprecise quantity like ‘large’, ‘medium’, ‘high’ etc. with a degree of belongingness to it. Typically, the value ranges between [0, 1].

Fuzziness in a fuzzy set is characterized by its membership functions. It classifies the element in the set, whether it is discrete or continuous. The membership functions can also be formed by graphical representations. The graphical representations may include different shapes.There are different methods to form membership functions. From literature [142,156,157,159] it was clearly noted that, a fuzzy set is completely characterized by its membership function (MF). Theoretically, a fuzzy set F of universe of discourse X = {x} is defined as a mapping, $\mu_F(\mathrm{x}) : \mathrm{X} \rightarrow [0, \alpha]$ , by which each x is assigned a number in the range $[0, \alpha]$, indicating the extent to which x has the attribute F. Thus, if x is the number of vehicles in a queue, “small” may be considered as a particular value of the fuzzy variable “queue” and each x is assigned a number in the range from 0 to $\infty$, $\mu_{small}(\mathrm{x}) \in [0, \alpha]$, that indicates the extent to which that x is considered to be small: $\mu_{small}(\mathrm{x}) \in [0, \alpha]$ is called a membership function. Various types of membership functions, along with their function and characteristics are presented in Table 4.2 and graphical representation of desired membership functions are represented in Figure 4.2.

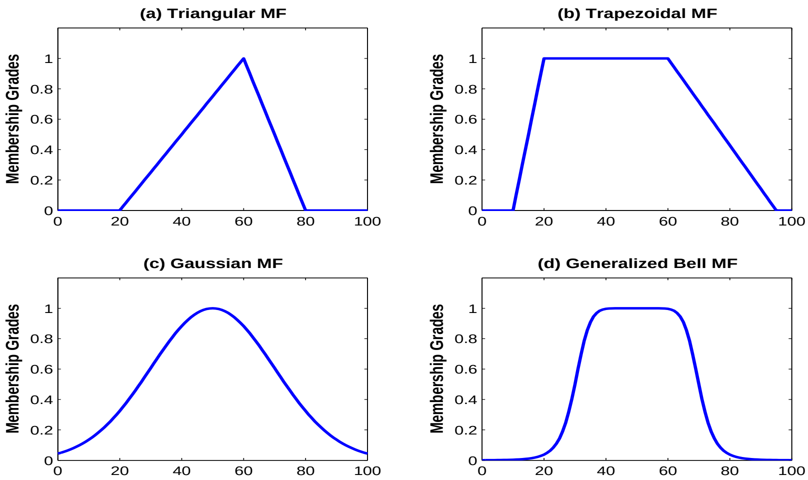
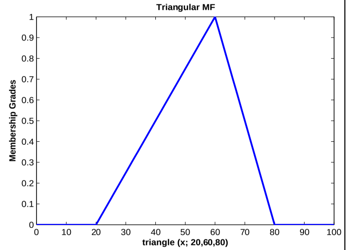
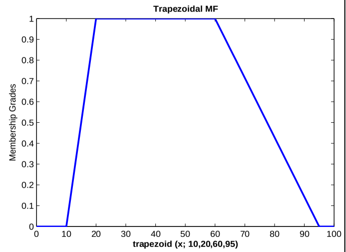
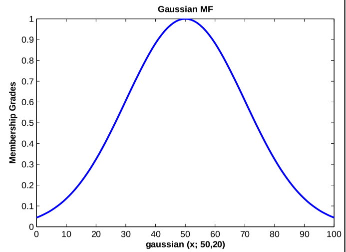
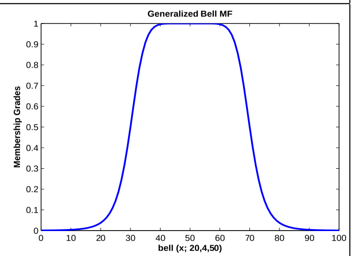



Figure 4.2: Examples of four classes of parameterized MFs: (a) triangle (x; 20,60,80); (b) trapezoid (x; 10,20,60,95); (c) Gaussian (x; 50,20) ; (d) bell (x; 20,4,50).

Table 4.2: Membership Functions

| Membership Function Name | Mathematical Expression | Characteristics of the Function | Graphical represents of the Membership functions |
|---|---|---|---|
| A triangular membership function | A triangular membership function is specified by three parameters $\{a, b, c\}$ as follows: $$triangle\,(x;\ a,\ b,\ c) = \left\{\begin{array}{cc} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c. \\ 0, & c \leq x \end{array}\right\}$$ $$triangle\,(x;\ a,\ b,\ c) = \max\left(\min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b}\right),\ 0\right)$$ | The parameters $\{a, b, c\}$ (with $a<b<c$ ) determine the x coordinates of the three corners of the underlying triangular MF. |   |
| A trapezoidal membership function | A trapezoidal membership function is specified by four parameters $\{a, b, c, d\}$ as follows: $$trapezoid\,(x;\ a,\ b,\ c,\ d) = \left\{\begin{array}{cc} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{array}\right\}$$ $$trapezoid\,(x;\ a,\ b,\ c,\ d) = \max\left(\min\left(\frac{x-a}{b-a},\ 1,\ \frac{d-x}{d-c}\right),\ 0\right)$$ | The parameters $\{a, b, c, d\}$ (with a $<$ b $\leq$ c $<$ d) determine the x coordinates of the four corners of the underlying trapezoidal membership function. Due to their simple formulas and computational efficiency, both triangular membership function and trapezoidal membership function have been used extensively, especially in real-time implementations. However, since the MFs are composed of straight line segments, they are not smooth at the corner points specified by the parameters. |   |
| A gaussian membership function | A gaussian membership function is specified by the two parameters {c,$\sigma$} $gaussian\,(x;\ c, \sigma) = e^{-1/2\left(\frac{x-c}{\sigma}\right)^2}$ | A gausian membership function is determined completely by c and $\sigma$; c represents the membership functions center and $\sigma$ determines the membership functions width. |   |
| A generalized bell membership function | A generalized bell membership function is specified by three parameters {a,b,c} $bell(x;\ a, b, c) = \frac{1}{1 + \left\lvert\frac{x-c}{a}\right\rvert^{2b}}$ | Where the parameter b is usually positive. (If b is negative , the shape of this MF becomes an upside-down bell.) |   |

### 4.2.2 Knowledge base

Knowledge base: The main part of the fuzzy system is knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules where as the rule base contains a number of fuzzy if-then rules. The formation of rule-base is discussed in the following manner:

Let X be the universe of discourse and x is the elements of X. A fuzzy set A in a universe of discourse X is characterized by a membership function $\mu_A$(x) which has a value ranging from 0 to 1. If there were 'n', fuzzy sets associated with a given input x, then fuzzifier would produce 'n' fuzzy sets as $A_1$(x), $A_2$(x)... $A_n$(x) with 'n' number of membership function$\mu_{A_i}(x)$, i =1, 2...n. This process is called the fuzzification. After fuzzification, the information goes to knowledge base, which comprises a database and rule base. Membership functions of the fuzzy sets are contained in the database. The rule base is a set of linguistic statements in the appearance of IF-THEN rules with antecedents and consequents, correspondingly, with AND or OR operators. In general, a fuzzy model, with multi-input multi-output (MIMO) system can be represented by the fuzzy IF-THEN rules connected by the AND operator with r antecedents, s consequents and m rules as:

$$\begin{aligned}
&\textbf{IF}\ X_1\ is\ B_{11}\ \textbf{AND}\ X_2\ is\ B_{12}\ \textbf{AND}\ \textbf{.....}\ \textbf{AND}\ X_r\ is\ B_{1r}\\
&\textbf{THEN}\ Y_1\ is\ D_{11}\ \textbf{AND}\ \ Y_2\ is\ D_{12}\ \textbf{AND}\ \textbf{...}\ \textbf{AND}\ \ Y_s\ isD_{1s}\\
&\textbf{ALSO}....\\
&\textbf{ALSO}\\
&\textbf{IF}\ X_1\ is\ B_{m1}\ \textbf{AND}\ X_2\ is\ B_{m2}\ \textbf{AND}\ \textbf{.....}\ \textbf{AND}\ X_r\ is\ B_{mr}\\
&\textbf{THEN}\ Y_1\ is\ D_{m1}\ \textbf{AND}\ \ Y_2\ is\ D_{m2}\ \textbf{AND}\ \textbf{...}\ \textbf{AND}\ \ Y_s\ is\ D_{ms}
\end{aligned} \tag{4.1}$$

Where $X_1$, $X_2$... $X_r$ are the input variables and $Y_1$, $Y_2$...... $Y_s$ are the output variables, $B_{ij}$ (i=1....m; j=1....r) and $D_i$ (i=1,....s) are the linguistic labels defined as reference fuzzy sets over the input space $X_1$, $X_2$... $X_r$and output space $Y_1$, $Y_2$...... $Y_s$ of the MIMO system. Conceptually, a MIMO fuzzy system can be decomposed into several multi-inputs single-output (MISO) system. Hence, in a system with s outputs, each multi-consequent rule is broken into s single-consequent rules. If the outputs $Y_1$, $Y_2$...... $Y_s$are independent variables, then the MIMO system can be decomposed into a collection of s MISO system as following manner[163–166]:

$$\begin{array}{l}
\textbf{IF} X_1 \ is \ B_{11} \ \textbf{AND} \ X_2 \ is \ B_{12} \ \textbf{AND} \ \ldots.. \ \textbf{AND} \ X_r \ is \ B_{1r} \ \textbf{THEN} \ Y_1 \ is \ D_1 \\
\textbf{ALSO} \ \ldots. \\
\textbf{ALSO} \\
\textbf{IF} \ X_1 \ is \ B_{m1} \ \textbf{AND} \ X_2 \ is \ B_{m2} \ \textbf{AND} \ \ldots.. \ \textbf{AND} \ X_r \ is \ B_{mr} \ \textbf{THEN} \ Y_s \ is \ D_s
\end{array} \tag{4.2}$$

After formation of rule base, the last block defuzzifier converts the fuzzy output obtained by inference engine into a non-fuzzy output real number domain and this process is called defuzzification. Among several methods of defuzzification, the Center of Area (COA) is the most widely used method [167–169].

### 4.2.3 Inference engine

The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined. It provides the process in which the system should behave to different inputs. Basically Inference Engine is a composition between fuzzy set. Widely Max-Min or Max-Product compositions are used. It is described as follows:

Let R be relation that relates elements from universe X to universe Y . Let S be the relation that relates elements from universe Y to universe Z . Let T relate the same element in universe that R contains to the same elements in the universe Z that S contains. The Max-Min complication is defined by the set-theoretic and membership function-theoretic expressions:

$$\begin{array}{l}
T = R \circ S \\
X_T(x,z) = \bigvee_{y \in Y} (X_R(x,y) \bigwedge X_S(y,z))
\end{array} \tag{4.3}$$

The max-product composition is defined by the set-theoretic and membership function-theoretic expressions

$$\begin{array}{l}
T = R \circ S \\
X_T(x,z) = \bigvee_{y \in Y} (X_R(x,y) \bullet X_S(y,z))
\end{array} \tag{4.4}$$

Using Max-Min and Max-Product compositations,Inference engine is built up with rule base. Let A fuzzy system with two non-interactive inputs $x_1$ and $x_2$ (antecedents) and a single output y (consequent) is described by a collection of "r" number of IF$-$THEN rules:

$$\textbf{IF} \ \ x_1 \ \ is \ \ A_k^1 \ \ and \ \ x_2 \ \ is \ \ A_k^2 \ \ \textbf{THEN} \ \ y^k \ \ is \ \ B^k, \ \ for \ \ k = 1, 2, ...r \tag{4.5}$$

where $A_k^1$ and $A_k^2$ are the fuzzy set representing $k^{th}$ antecedent pairs and $B^k$ is the fuzzy set representing $k^{th}$ consequent. The Max-Min Inference will be:

$$\mu_{B^k} = \underset{k}{max} \; [min[\mu_{A_1^k}(x_1), \mu_{A_2^k}(x_2)]] \tag{4.6}$$

The Max-Product Inference will be:

$$\mu_{B^k} = \underset{k}{max} \; [\mu_{A_1^k}(x_1) \bullet \mu_{A_2^k}(x_2)]] \tag{4.7}$$

### 4.2.4 Defuzzifier

The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input fuzzifier block.

Defuzzification is the process of converting the fuzzy variables to crisp value. The fuzzy results generated cannot be used directly, hence it is necessary to convert the fuzzy quantities into crisp quantities for further processing. This is achieved by using defuzzification process. In general, there are five methods for defuzzifying a fuzzy set A of a universe of discourse Z. This is as shown in Figure 4.3.A brief explanation of each defuzzification strategy is given below:

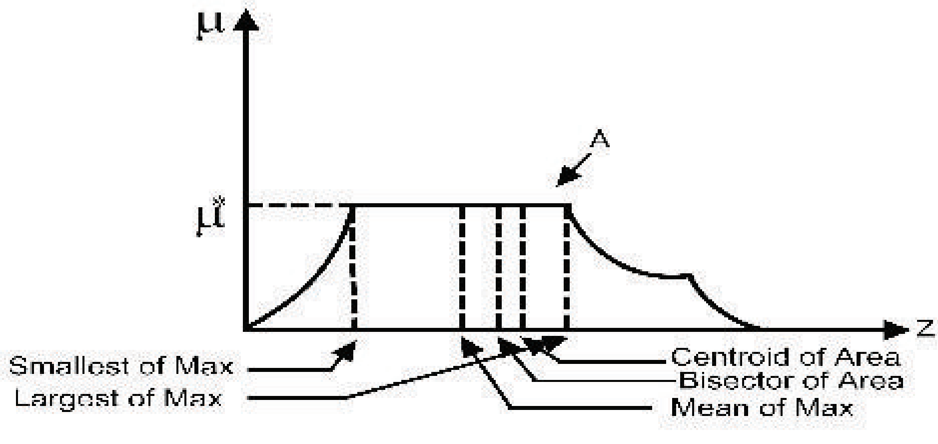



Figure 4.3: Various defuzzification schemes for obtaining a crisp output.

- **Centroid of area or Center of gravity** :

$$^{z}COA = \frac{\int_Z \mu_A(z)zdz}{\int_Z \mu_A(z)dz} \tag{4.8}$$

Where $\mu_A$(z) is the aggregated output membership function. This is the most widely adopted defuzzification strategy, which is reminiscent of the calculation of expected values of probability distributions.

- **Bisector of area or Center of average**:

$$\int_{\alpha}^{{}^{z}BOA} \mu_A(z)\, dz \;=\; \int_{{}^{z}BOA}^{\beta} \mu_A(z)\, dz \tag{4.9}$$

Where $\alpha = \min\{z|z \in Z\}$ and $\beta = \max\{z|z \in Z\}$. That is, the vertical line z=$^{z}$BOA partitions the region between z = $\alpha$, z=$\beta$, y=0 and y = $\mu_A$(z) into two regions with the same area.

- **Mean of Maximum**: $^{z}$MOM is the average of the maximining z at with the membership function each a maximum $\mu^*$. In symbols,

$${}^{z}MOM = \frac{\int_{Z'} z\; dz}{\int_{Z'} dz} \tag{4.10}$$

Where Z′ $\min\{z|\mu_A(z) = \mu^*\}$. The mean of maximum is the defuzzification strategy employed in Mamdani's fuzzy logic controllers [170, 171].

- **Smallest of maximum**: $^{z}$SOM is the minimum of the maximizing z.

- **Largest of maximum**: $^{z}$LOM is the maximum of the maximizing z. Because of their obvious bias $^{z}$SOM and $^{z}$LOM are not used as often as the other three defuzzification methods.

## 4.3 Types of Fuzzy Logic System

Two commonly used inference systems are i.e. Mamdani fuzzy model and Sugeno fuzzy model. Mamdani fuzzy model [170] is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent parameters. The benefit of this model is that an expert generally provides the rule base and hence to a certain degree it is translucent to explanation and study. Because of its ease, Mamdani model is still most commonly used technique for solving many real world problems. Takagi and Sugeno proposed Sugeno fuzzy model [172]; Sugeno and Kang [173] in an attempt to build up a methodical approach to generating fuzzy rules from a given input-output data. These models are built with if-then rules that have fuzzy antecedent and functional consequent. Typically, the consequent is a polynomial function of the desired input variables. When the order of the polynomial function is of first order, then the resulting fuzzy expert system is called the first order Sugeno or TSK fuzzy model, which was originally, purposed by Takagi and Sugeno [172]; Sugeno and Kang [173]. When the order of the polynomial function is zero or the consequent part is constant, then the system is called zero order Sugeno and TSK fuzzy model, in which each rule's consequent, is specified by a single value. To represent this constant output, a single spike is used, which is also known as singleton output membership function. The main advantage of the TSK model is its computational simplicity. There is another fuzzy model was available and named as Tsukamoto fuzzy inference system but it was not famous due to its high computational cost and poor performance [146].

### 4.3.1 Mamdani Fuzzy System

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed by Mamdani [170] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Zadeh's [154] paper on fuzzy algorithms for complex systems and decision processes. The inference engine and rule base in Mamdani Fuzzy System is represented as follows:

If x is $A_1$ and y is $B_1$ then Z is $c_1$
If x is $A_2$ and y is $B_2$ then Z is $c_2$

(where A and B are linguistic values defined by fuzzy sets on universe of discourse X and Y). A rule is also called a fuzzy implication, "x is A" and "y is B"are called the antecedent or premise and "z is C" is called the consequence or conclusion.Fig. 4.4. represents a two-rule based Mamdani fuzzy inference system, where overall output z is derived when subjected to two crisp inputs x and y. This figure represents a min-max inference system[170, 171].

### 4.3.2 Takagi Sugeno Kang (TSK) Fuzzy Model

The sugeno fuzzy model which is also known as the TSK fuzzy model was proposed by Takagi, Sugeno and Kang [172, 173] in an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set. A typically first order TSK fuzzy rule can be represented as
If x is $A_1$ and y is $B_1$ then z $= a_1x + b_1y + c_1$ .

If x is $A_2$ and y is $B_2$ then z $= a_2x + b_2y + c_2$ .

.

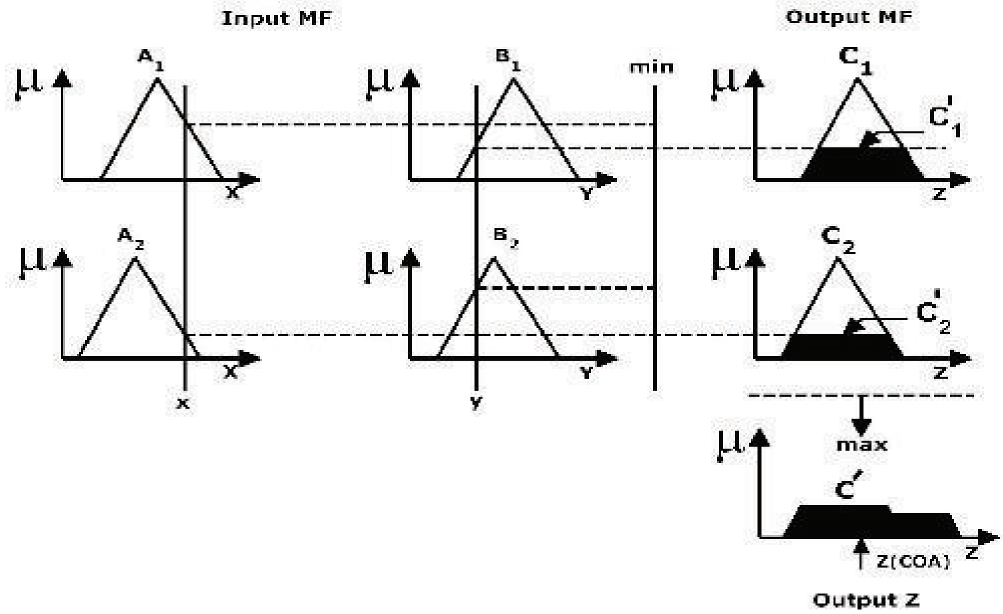



Figure 4.4: The Mamdani Fuzzy inference system using min-max operators.

.

If x is $A_n$ and y is $B_n$ then z $= a_n x + b_2 y + c_n$ .

Where A and B are fuzzy sets in the antecedent, while z=$f$(x,y) is a crisp function in the consequent. Usually $f$(x,y) is polynomial of the input variables x and y, but it can be any function as long as it can appropriately describe the output of the model within the fuzzy region specified by the antecedent of the rule. When $f$(x,y) is a first-order polynomial, the resulting fuzzy inference system is called a first-order Sugeno fuzzy model, which was originally proposed [172,173]. When $f$ is constant, then the system is a zero-order Sugeno fuzzy model, which can be viewed either as a special case of Mamdani fuzzy inference system, in which each rule's consequent is specified by a fuzzy singleton. Figure 4.5 shows the fuzzy reasoning procedure for a first-order Sugeno fuzzy model. Since each rule has a crisp output, the overall output is obtained via weighted average, thus avoiding the time-consuming process of defuzzification . In practice, the weighted average operator is sometimes replaced with the weighted sum operator (that is, z $=$ $w_1 z_1 + w_2 z_2$) to reduce computation further, especially in the training of a fuzzy inference system. Since the only fuzzy part of a Sugeno fuzzy model is in its antecedent, it is easy to demonstrate the distinction between a set of fuzzy rules and nonfuzzy ones.

### 4.3.3 Comparison Between Sugeno and Mamdani Method

The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. Also the difference lies in the consequents of their

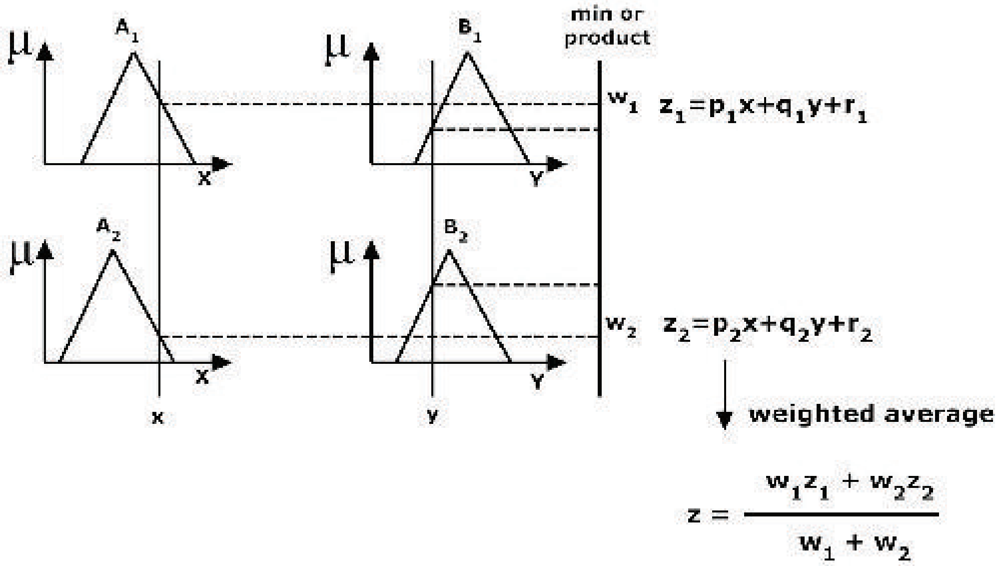



Figure 4.5: The Sugeno fuzzy model.

fuzzy rules, and thus their aggregation and defuzzification procedures differ significantly. The number of the input fuzzy sets and fuzzy rules needed by the Sugeno fuzzy systems depend on the number and locations of the extrema of the function to be approximated. In Sugeno method a large number of fuzzy rules must be employed to approximate periodic or highly oscillatory functions. The minimal configuration of the TS fuzzy systems can be reduced and becomes smaller than that of the Mamdani fuzzy systems if nontrapezoidal or nontriangular input fuzzy sets are used. Sugeno controllers usually have far more adjustable parameters in the rule consequent and the number of the parameters grows exponentially with the increase of the number of input variables. Far fewer mathematical results exist for TS fuzzy controllers than do for Mamdani fuzzy controllers, notably those on TS fuzzy control system stability. Mamdani is easy to form compared to Sugeno method [174]. Fuzzy Inference system is the most important modeling tool based on fuzzy set theory. The FISs are built by the domain experts and are used in automatic control, decision analysis and various other experts systems [144, 153, 175].

## 4.4 Artificial Neural Network (ANN)

An artificial neural network is motivated by the theory of operation of biological neurons. Neural Network (NN) represents an important paradigm for classifying patterns or approximating complex non-linear process dynamics. These properties indicate that NN exhibit some intelligent behavior and are good candidate models for non-linear processes, for which no perfect mathematical model is available. Every artificial neural network model is designed as per the learning process and in general, the learning can be broadly classified into three categories: supervised learning, unsupervised learning and reinforcement learning. Supervised learning requires a trainer, who supplies the input–output training instances. The learning system adapts its parameters by using algorithms that generate the desired output patterns for a given input pattern. In the absence of trainers, the desired output for a given input instance is not known and consequently the learner has to adapt its parameters autonomously. Such type of learning is termed "unsupervised learning". The third type called the reinforcement learning bridges a gap between supervised and unsupervised categories. In reinforcement learning, the learner does not explicitly know the input–output instances, but it receives some form of feedback from its environment. The feedback signals help the learner to decide whether its action on the environment is rewarding or punishable. Thus, the learner adapts its parameters based on the states (rewarding/punishable) of its actions[176–179].

A neural network is a collection of small individually interconnected processing units. Information is passed through these units along interconnections. An incoming connection has two values associated with it, an input value and a weight. The output of the unit is a function of the weighted sum. ANNs implemented on computers are not programmed to perform specific tasks. Instead, they are trained with respect to data sets until they learn patterns used as inputs. Once trained, new patterns may be presented to them for prediction or classification. ANNs can automatically learn to recognize patterns in data from real systems or from physical models, computer programs, or other sources. An ANN can handle many inputs and produce answers that are in a form suitable for designers [178,180]. ANNs can be considered as simplified mathematical models of brain-like systems and they function as parallel-distributed computing networks. However, in contrast to conventional computers, which are programmed to perform specific task, most neural networks must be taught or trained. They can learn new associations, new functional dependencies and new patterns. Neural networks obviate the need to use complex mathematically explicit formulas, computer models and impractical and costly physical models. Some of the characteristics that support the success of ANNs and distinguish them from the conventional computational techniques are [180, 181]:

All neural network models, proposed over the years, share a common building block, known as a neuron and a networked interconnection structure [178, 180, 182]. The most widely used neuron model is based on McCulloch and Pitts' work [178] and is illustrated in Fig.4.6. The neuron consists of two parts: the net function and the activation function. The net function provides weighted linear combination.

$$\mathrm{z} = \sum_{i=1}^{N} w_i x_i + \theta \tag{4.11}$$

Parameters $\{ \mathrm{w}_i{:}1 \leq \mathrm{i} \leq \mathrm{N} \}$ are known as synaptic weights. The quantity $\theta$ is called

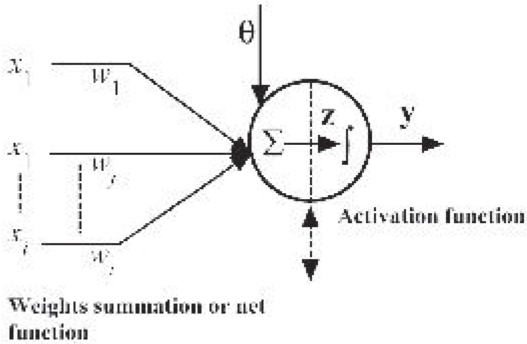



Figure 4.6: The basic neuron

the bias (or threshold) and is used to model the threshold. In literature, many other types of network input combination methods have been proposed. These are summarized in Table 4.3

Table 4.3: Summary of net function

| Net Function | Formula | Comments |
| --- | --- | --- |
| Linear | z $= \sum_{i=1}^{N} w_i x_i + \theta$ | Most Commonly used |
| Higher Order | z $= \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} x_i x_k + \theta$ | $x_i$ is a weighted linear combination of their order polynomial terms. |
| Delta ($\sum$, $\prod$) | z $= \prod_{i=1}^{N} w_i x_i$ | Seldom used for the input variables. The number of input terms equal N$^d$, where d is the order of the polynomial. |

The output of the neuron, denoted by $y_i$ is related to the network input $x_i$ via a linear or nonlinear transformation called the activation function; y $= f$(z). In various neural network models, different activation functions have been proposed. The most commonly used activation functions are summarized in Table 4.4. Table 4.4 lists both the activation functions as well as MATLAB function. In a neural network, multiple neurons are interconnected to form a network to facilitate distributed computing.Neural networks have been a powerful tool for different engineering applications more than last two decades [183–192]. Different types of artificial neural network models are discussed in the following sections:

Table 4.4: Transfer or Activation Functions

| Name | Input/Output Relation | MATLAB Function |
|---|---|---|
| Hard Limit | $a = 0 \;\; n < 0$<br>$a = 1 \;\; n \geq 0$ | hardlim |
| Symmetrical Hard Limit | $a = -1 \;\; n < 0$<br>$a = +1 \;\; n \geq 0$ | hardlims |
| Linear | $a = n$ | purelin |
| Saturating Linear | $a = 0 \quad n < 0$<br>$a = n \quad 0 \leq n \leq 1$<br>$a = 1 \quad n > 1$ | satlin |
| Symmetric Saturating Linear | $a = -1 \quad n < -1$<br>$a = n \quad -1 \leq n \leq 1$<br>$a = 1 \quad n > 1$ | satlins |
| Log-Sigmoid | $a = \frac{1}{1+e^{-n}}$ | logsig |
| Hyperbolic Tangent Sigmoid | $a = \frac{e^{n}-e^{-n}}{e^{n}+e^{-n}}$ | tansig |
| Positive Linear | $a = 0 \;\; n < 0$<br>$a = n \;\; 0 \leq n$ | poslin |
| Competitive | $a$ =1 neuron with max $n$<br>$a$ =0 all other neurons | compet |

### 4.4.1 Multilayer Perceptron

Multilayer perceptron (feed-forward) networks consist of units arranged in layers with only forward connections to units in subsequent layers [180]. The connections have weights associated with them. Each signal traveling along the link is multiplied by a connection weight. The first layer is the input layer, and the input units distribute the inputs to units in subsequent layers. In subsequent layers, each unit sums its inputs, adds a bias or threshold term to the sum and nonlinearly transforms the sum to produce an output. This nonlinear transformation is called the activation function of the unit. The output layer units often have linear activations. In the remainder of this section, linear output layer activations are assumed. The layers sandwiched between the input layer and output layer are called hidden layers and units in hidden layers are called hidden units [179–181, 193–199]. Such a network is shown in Fig. 4.7. The training data set consists of $N$ training patterns $\{x_p, t_p\}$, where p is the pattern number. The input vector $x_p$ and desired output vector $t_p$ have dimensions $N$ and $M_0$ respectively; $y_p$ is the network output vector for the $p^{th}$ pattern. The thresholds are handled by augmenting the input vector with an element $x_p(N + 1)$ and setting it equal to one.

For the $j^{th}$ hidden unit, the net input $net_p(j)$ and the output activation $O_p(j)$ for the $p^{th}$ training pattern are:

$$net_p(j) = \sum_{i=1}^{N+1} w(j, i)xp(i) \tag{4.12}$$

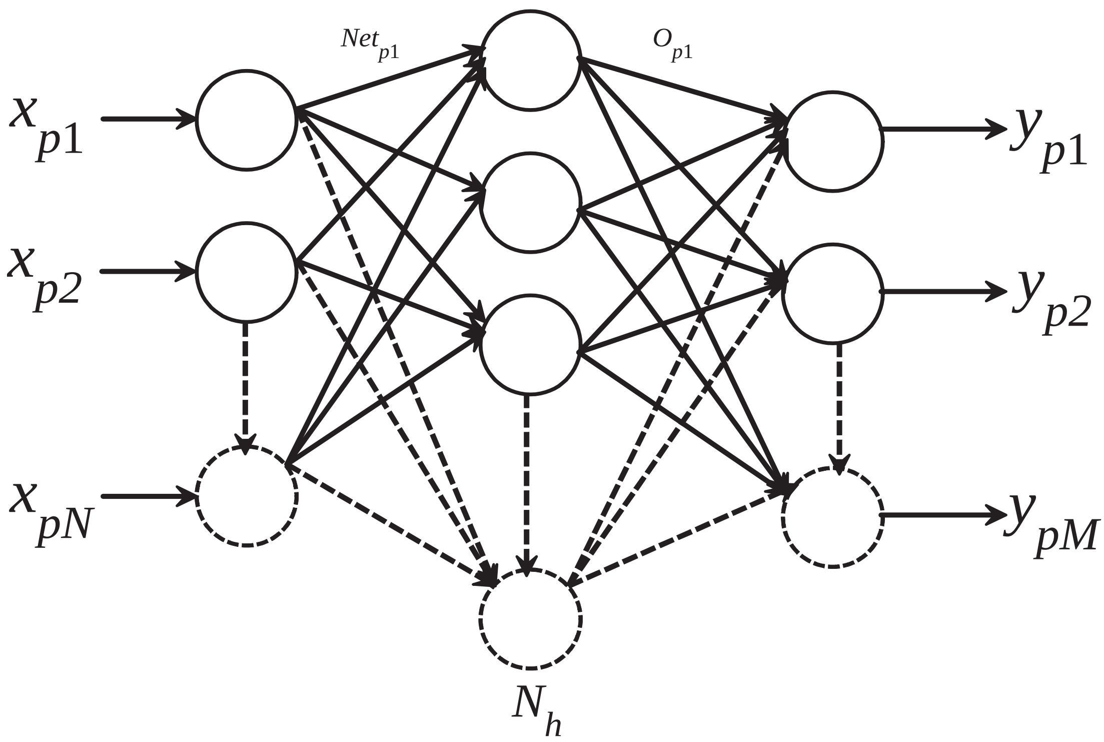



Figure 4.7: Feed-forward neural network

Where $1 \leq j \leq N_h$

$$O_p(j) \;=\; f(net_p(j)) \tag{4.13}$$

where *w(j, i)* denotes the weight connecting the $i^{th}$ input unit to the $j^{th}$ hidden unit. For MLP networks, a typical activation function f is the sigmoid, given by

$$f\left(net_p(j) \;=\; \frac{1}{1+\;\exp(-net_p(j))}\right) \tag{4.14}$$

For trigonometric networks, the activations can be the sine and cosine functions. The $k^{th}$ output for the $p^{th}$ training pattern is $y_{pk}$ and is given by

$$y_{pk} = \sum_{i=1}^{N+1} w_{i0}(k,i)\, x_p(i) \;+\; \sum_{j=1}^{N_h} w_{h0}(k,j)\, O_p(j) \tag{4.15}$$

Where $1 \leq$ k $\leq$ M where $w_{io}(k,i)$ denotes the output weight connecting the $i^{th}$ input unit to the $k^{th}$ output unit and $w_{ho}(k,j)$ denotes the output weight connecting the $j^{th}$ hidden unit to the $k^{th}$ output unit. The mapping error for the $p^{th}$ pattern is

$$E_p = \sum_{k=1}^{N_P} (t_{pk} -\; y_{pk})^2 \tag{4.16}$$

where $t_{pk}$ denotes the $k^{th}$ element of the $p^{th}$ desired output vector. In order to train a neural network in batch mode, the mapping error for the $k^{th}$ output unit is defined as

$$E(k) = \frac{1}{N_v} \sum_{p=1}^{N_v} (t_{pk} - y_{pk})^2 \tag{4.17}$$

The overall performance of an MLP neural network, measured as mean square error (MSE), can be written as

$$E = \sum_{k=1}^{M} E(k) = \frac{1}{N_p} \sum_{p=1}^{N_v} E_p \tag{4.18}$$

The key distinguishing characteristic of the multilayer feed-forward neural networks (MFNN) with the backpropagation learning algorithm is that it forms a nonlinear mapping from a set of input stimuli to a set of outputs using features extracted from the input patterns. The neural network can be designed and trained to accomplish a wide variety of nonlinear mappings, some of which are very complex. This is because the neural units in the neural network learn to respond to features found in the input. By applying the set of formulations of the BP algorithm obtained in the previous sub-section, a calculation procedure of such a learning process is summarized as follows[180, 181, 193, 194]:
Given a finite length input pattern $x_1(k)$, $x_2(k)$ . . . . $x_n(k)$ $\in$ R ($1 \leq k \leq K$)

*Step* 1: Select the total number of layers $M$, the number $n_i$($i$ =1,2, . . . , $N$-1) of the neurons in each hidden layer, and an error tolerance parameter $\varepsilon > 0$.

*Step* 2: Randomly select the initial value of the weight vectors $W_{aj}^{(i)}$ for $I$= 1,2, . . . $M$and $j$ =1,2, . . . ,$n_i$.

*Step* 3: Initialization $W_{aj}^{(i)} \leftarrow W_{aj}^{(i)}(0)$, and $k \leftarrow 1$.
*Step* 4: Calculate the neural outputs:

$$\begin{cases} S_j^{(i)} = \left(W_{a_j}^{(i)}\right)^T X_a^{(i-1)} \\ X_j^{(i)} = \sigma\,(S_j^{(i)}) \end{cases}$$

for $I$= 1,2, . . . ,$M$and $j$ =1,2, . . . ,$n_i$.

*Step* 5: Calculate the output error $e_j = d_j - X_j^{(M)}$ for $j$ =1,2, . . . ,$m$.
*Step* 6: Calculate the output delta's

$$\delta_j^{(M)} = e_j\ \sigma'(S_j^{(M)})$$

*Step* 7: Recursively calculate the propagation errors of the hidden neurons:

$$e_j^{(i)} = \sum_{l=1}^{n_i+1} \delta_l^{(i+1)} \, W_{lj}^{(i+1)}$$

from the layer $M$-1, $M$-2, ..... to layer 1.

*Step* 8: Recursively calculate the hidden delta values:

$$\delta_l^{(i)} = e_l^{(i)} \sigma'(S_l^{(i)})$$

*Step* 9: Update weight vector:

$$W_{a_j}^{(i)} = \; W_{a_j}^{(i)} \; + \; \eta \delta_j^{(i)} X_a^{(i-1)}$$

*Step* 10: Calculate the error function

$$E = \; E \; + \; \frac{1}{k} \sum_{j}^{m} e_j^2$$

*Step* 11: if $k = K$then go to step 12; otherwise $k \leftarrow k$+1 and go to step 4.
*Step* 12: if $E \quad \leq \quad \varepsilon$ then go to step 13; otherwise go to step 3.
*Step* 13: Learning is completed. Output the weights.

In the procedure listed above, several learning factors such as the initial weights, the learning rate, the number of the hidden neural layers and the number of neurons in each layer, may be reselected if the iterative earning process does not converge quickly to the desired point. Although, the BP learning algorithm provides a method for training MFNNs to accomplish a specified task in terms of the internal nonlinear mapping representations.

### 4.4.2 Radial Basis Function Network (RBFN)

The structure of Radial Basis Function Network (RBFN) is presented in Figure 4.8. It consists of three layers viz: the input layer, the non-linear hidden layer and linear output layer. The hidden layer computes a non-linear function of input and the output layer provides linear combination of hidden layer. A RBFN [200–205] is linear in its parameters, therefore once suitable basis function parameters have been chosen, it can be trained using a linear supervised training scheme.

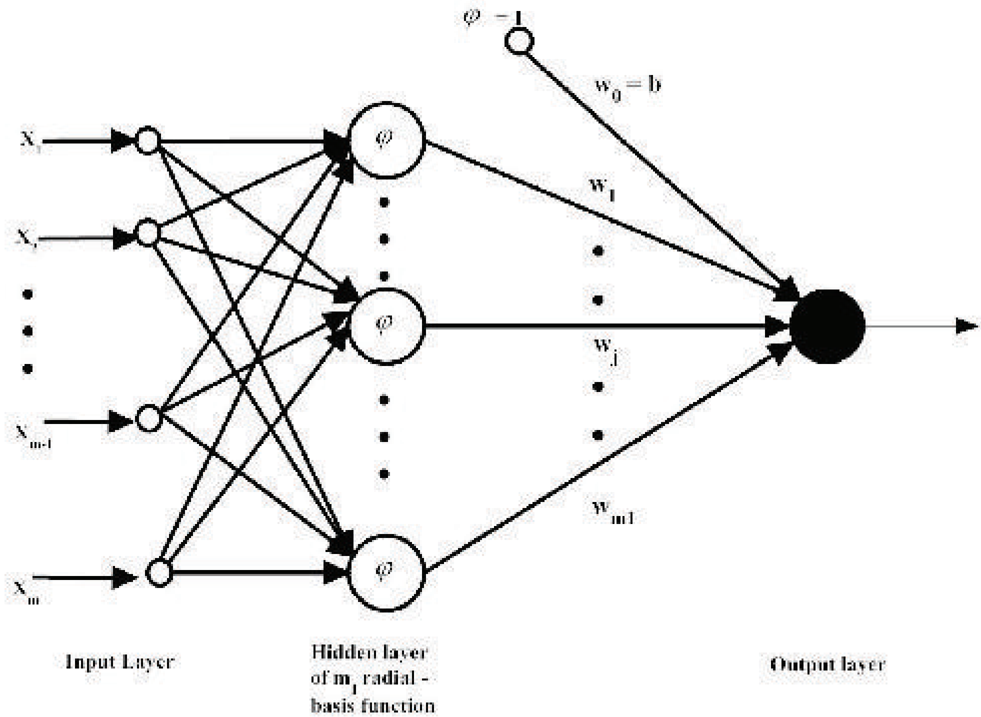



Figure 4.8: Radial Basis Function Network

A RBFN with M kernels, or hidden units, has the overall response function given by:

$$f(x(n)) \ = \sum_{i=1}^{M} w_i \phi_i \left(n\right) \tag{4.19}$$

where x (n) is a vector in the input space of the RBFN, $\phi_i(n)$ is the response function of the i$^{th}$ kernel, and $w_i$ is the weight associated with the i$^{th}$ kernel. The most common nonlinear kernel function used in RBFNs is the Gaussian function, which can be represented as

$$\phi_i \left(n\right) \ = \exp\left[\frac{- \left\|x(n) \ - \ c_i\right\|^2}{2\sigma_i^2}\right] \quad i \ = \ 1, \ 2, \ldots, \ M \tag{4.20}$$

where || . || is the Euclidean distance[1] measure, c$_i$ is the position of the i$^{th}$ kernel's centre in the input space of the RBFN, and $\sigma_i$ is known as the width of the i$^{th}$ kernel. The type of nonlinear kernel function is not crucial for the performance of the RBFN [180].

Training of RBF includes setting the centers, fixing spread parameters and the associated weights. The three most popular training methods are [180, 202]:

[1]Euclidean Distance: Let P= (P$_1$, P$_2$, ... P$_n$) and Q = (Q$_1$, Q$_2$, ... Q$_n$) are the data points, then Euclidean distance will be $\sqrt{\sum_{i=1}^{n} (P_i - Q_i)^2}$

- Fixed centers selected at random
- Self-organized selection of centers (K-mean)
- Supervised selection of centers

A universal kernel width can be used (i.e. the same width for each kernel): $\sigma_i = \sigma$; i = 1,2,... M. The following equation is used to calculate the width $\sigma$:

$$\sigma = \frac{d_{ME}}{\sqrt{2M}} \tag{4.21}$$

where $d_{ME}$ is the maximum Euclidean distance between any two centers, and M is the number of kernels. Such a choice for $\sigma$ in RBFN ensures that the Gaussian kernel functions are neither too peaked nor too flat [180]. Once the centers and widths of the M kernel functions have been selected, the M output layer weights $w_i$; i = 1, 2, ... M, can be trained using a supervised linear least-squares technique (LMS). In many literature, the centers of the RBF network are chosen using K-mean clustering [206, 207].Fuzzy c-mean clustering also may be used for selecting centers for RBF.

#### 4.4.2.1 The K-means Algorithm

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroid, one for each cluster. This algorithm aims at minimizing an objective function, in this case a squared error function [206,207]. The objective function is:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^j - c_j \right\|^2 \tag{4.22}$$

where $\left\| x_i^j - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$and the cluster centre $c_j$, is an indicator of the distance of the $n$ data points from their respective cluster centers. The algorithm is composed of the following steps:

Suppose there is ‘n’ number sample feature vectors $\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$ all from the same class, and they fall into k compact clusters, k < n. Let $\mathbf{m}_i$ be the mean of the vectors in cluster i. If the clusters are well separated, a minimum-distance classifier is used to separate them. It can be said that $\mathbf{x}$ is in cluster i if $|| \mathbf{x} - \mathbf{m}_i||$ is the minimum of all the k distances. The following procedure for finding the k means is suggested:

- Make initial guesses for the means $\mathbf{m}_1$, $\mathbf{m}_2$, ..., $\mathbf{m}_k$
- Until there are no changes in any mean

  - ⋆ Use the estimated means to classify the samples into clusters
  - ⋆ For i from 1 to k
    - ∗ Replace $\mathbf{m}_i$ with the mean of all of the samples for cluster i
  - ⋆ end_for
- end_until

#### 4.4.2.2 Algorithm for Radial Basis Function Network

**Step 1**: The centers ($M_i$, i=1, 2, 3,..n) are chosen randomly and updated by applying K-mean clustering algorithm and an error tolerance parameter $\varepsilon$ (0.01) > 0. This algorithm (K-mean) aims at minimizing an objective function, in this case a squared error function. The objective function is:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left(\left\|X_i^j - C_j\right\|^2\right) \tag{4.23}$$

where $\left\|x_i^j - c_j\right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$and the cluster centre$c_j$, is an indicator of the distance of the $n$ data points from their respective cluster centers.

**Step 2**: Initial values of the weight is selected at random. $w_{i,j}$ , for i=1, 2,... $M_i$, are chosen.

**Step 3**: **Initialization** All the weights $w_{i,j}^m$ are initialized to random number and given as $w_{i,j}^m(0)$

$$w_{i,j} \leftarrow w_{i,j}(0) \tag{4.24}$$

**Step 4: Calculation of the RBFN outputs**

After selecting centers, intializing weights, Gaussian radial functions are used to determine the network output and are given by:

$$y_j = \sum_{j=1}^{k} w_{i,j} \times \ \phi\left(\left\|X_i^j - C_j\right\|\right) \tag{4.25}$$

Where $y_j$ is the output of RBF model and K is the training samples.

$$u_i = \phi\left(\left\|X_i^j - C_j\right\|\right) \ = \sum_{i=1}^{M} \exp\left(\frac{\left\|X_i^j - C_j\right\|}{2\sigma_i^2}\right) \tag{4.26}$$

**Step 5: Calculation of the output error**

The error is calculated as follows:

$$\begin{aligned} E &= \sum_{j=1}^{K} (d_j \ - y_j)^2 \\ &= e_j \cong d_j \ - y_j \\ &= d_j - \sum_{j=1}^{K} \sum_{i=1}^{M} w_{i,j} \times \ \exp\left(\frac{\|X_i - C_i\|}{2\sigma_i^2}\right) \end{aligned} \tag{4.27}$$

Where $d_j$ is the desired output and $y_j$ is the output of RBF model.

**Step 6: Updating the weight vectors**

The weight matrices are updated next using the following relationship

$$w_{i,j}^{new} = w_{i,j}^{old} + \eta u_i e_j \tag{4.28}$$

**Step 7:** If error $\leq \ \ \varepsilon$ (0.01) then go to Step 8, otherwise go to Step 3.

**Step 8:** After the learning is complete, the weights are fixed and the network can be used for testing.

After training the weights are fixed for testing the model. If the testing results are not perfect, then the training process is continued until the desired performance measure is achieved.

## 4.5 Adaptive Network based Fuzzy Inference System (ANFIS)

The ANFIS has proven to be an excellent function approximation tool. The ANFIS structure was proposed by Jang in 1993 [208].Figure 4.9 shows a typical ANFIS structure with two inputs (x and y) and one output $f$. ANFIS implements a first-order Sugeno-style fuzzy system [175, 209, 210].

**Layer 1**: Every node of this layer is a square node expressed with node function;

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1, 2 \tag{4.29}$$

$$O_{1,i} = \mu_{B(i-2)}(y), \quad i = 3, 4 \tag{4.30}$$

$$\mu_{A_i}(x) \ = \ \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{4.31}$$

Where $x_1$ or $x_2$ is input of the node, $A_i$ (or $B_{(i-2)}$) is the language variable correlated with this node function value. $O_{1,j}$ is the degree of membership function (MF) of A ($A=A_1$, $A_2$ $B_1$ $B_2$). Usually in ANFIS, bell shaped membership is selected. The membership

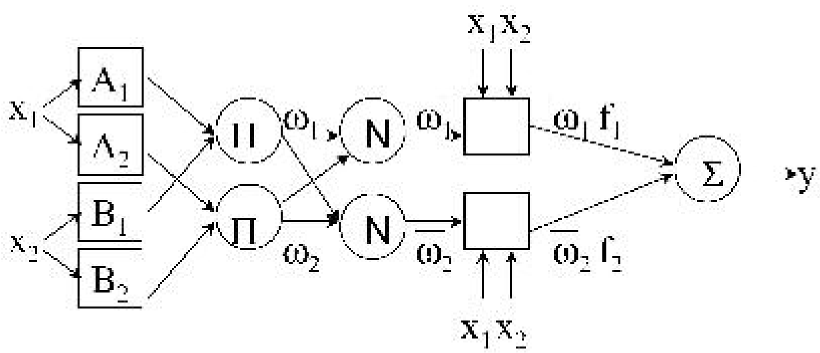



Figure 4.9: Architecture of ANFIS

function $\mu_{Ai}$(x) with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i}(x) \;=\; \exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\} \tag{4.32}$$

Where {$a_i b_i$, $c_i$} is the parameters set that changes the shape of the MF which are referred to as premise parameters.

**Layer 2**: Every node of this layer is a circle node labeled $\prod$ which multiplies the incoming signals and send to output. For instance

$$O_{2,i} \;=\; w_i = \;\mu_{A_i}(x) \;\times\; \mu_{B_i}(y), \quad i = 1,2 \tag{4.33}$$

Each node output represents the firing strength of rule.

**Layer 3**: Every node of this layer is a circle node labled N, the ith node calculates the ratio of the i$^{th}$ rule's firing strength to the sum of all rules firing strengths:

$$O_{3,i} \;=\; \overline{w}_i f_i = \;\frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{4.34}$$

For convenience, outputs of this layer are called normalized firing strengths.

**Layer 4**: Every node i in this layer is adaptive node, and the output is

$$O_{4,i} \;=\; \overline{w}_i f_i = \;\overline{w}_i(p_i x \;+\; q_i y \;+\; r_i) \quad i = 1,2 \tag{4.35}$$

Where {$p_i q_i$, $r_i$} is the parameter set which are refered to as consequent parameters.

**Layer 5**: Every node of this layer is a fixed node labeled $\sum$ that computes the overall output as the summation of all the input signals

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{4.36}$$

The similar network structures were also proposed independently by Lin and Lee and Wang and Mendel [208].

## 4.6 Conclusion

Soft-Computing techniques such as Fuzy Logic, Neural Network etc. are computational systems that do not require programming in a conventional sense, but can learn and generalize from training examples. Soft-Computing is therefore potentially simple to apply and has generated a great deal of interest in engineering. Soft-computing based models were successfully implemented in prediction of traffic noise, prediction of noise annoyance and noise-induced hearing loss. However, no such applications of soft-computing models were found in opencast mining machineries noise prediction. However, it was found that mathematical models had poor performance in non-stationary problem, where Soft Computing models have better performance. Therefore Soft-Computing methods are suitable replacements of mathematical noise prediction models as the data set collected or measured from machineries were purely non-stationary in nature. The next chapter highlights the application of Soft-Computing methods for prediction of opencast mining machineries noise.

# CHAPTER 5

# SOFT COMPUTING TECHNIQUES FOR NOISE PREDICTION IN OPENCAST MINES

## 5.1 Introduction

Noise is generated from almost all opencast mining operations. Noise is generated from different fixed, mobile and impulsive sources; thereby becoming an integral part of the mining environment. With increased mechanization, the problem of noise has got accentuated in opencast mines. Prolonged exposure of miners to the high levels of noise causes noise induced hearing loss besides several non-auditory health effects [3]. The impact of noise in opencast mines depends on the sound power level of the noise generators, prevailing geo-mining conditions and the meteorological parameters of the mines [108,111,115]. The noise levels need to be studied as an integrated effect of the above parameters. In mining scenario, the equipment conditions and environment continuously change as the mining activity progresses. Depending on their placement, the overall mining noise emanating from the mines varies in quality and level. Thus for environmental noise prediction modeling, the noise level at any receiver point needs to be resultant sound pressure level of all the observation locations.

The need for accurately predicting the level of sound emitted in opencast mines is well established. Some of the noise forecasting models used extensively in Europe are those of the German Draft Standard VDI-2714, Outdoor Sound Propagation and Environmental Noise Model (ENM) of Australia [9]. These models are generally used to predict noise in petrochemical complexes and mines. The algorithm used in these models rely to a great extent on interpolation of experimental data. But their applications are limited to sites which are more or less similar to those for which the experimental data were assimilated.

A number of models were developed and extensively used for the assessment of sound pressure level and their attenuation around industrial complexes. Generally in Indian mining industry, Environmental Noise Model developed by RTA (Renzo Tonin & Associates Pty Ltd) group, Australia is mostly used to predict noise [110, 115]. ENM was used to predict sound pressure level in mining complexes at Moonidih Project in Jharia Coalfield, Dhanbad, India [110]. The applied model output was represented as noise contours. The application of different noise prediction models was studied for various mines and petrochemical complexes and it was reported that VDI2714 model was the simplest and least complex model vis-à-vis other models [9]. VDI2714 and ISO (1996) noise prediction models were used in Assiut cement plant, Assiut cement quarry and El-Gedida mine at El-Baharia oasis of Egypt to predict noise. From the study, it was seen that the prediction models could be used to identify the safe zones with respect to the noise level in mining and industrial plants. It was also inferred that the VDI2714 model is the simplest model for prediction of noise in mining complexes and workplace [116]. Air attenuation model was developed for noise prediction in limestone quarry and mines of Ireland and was applied to predict attenuation in air due to absorption [114].

In the empirical models, all influences are taken into account regardless of whether or not they can be separately recognized. This is the main advantage of these models. However, the accuracy of these models depends on the accuracy of the measurements, similarities between the conditions where the noise attenuation is analyzed and the conditions where the measurements are carried out, and the statistical method that is used to make the empirical model. The deterministic models are based on the principles of physics of sound and therefore, can be applied in different conditions without affecting the accuracy. But their implementation usually requires a great database of meteorological characteristics such as atmospheric temperature, humidity, wind and so on, which is nearly difficult to obtain. Hence, the implementation of the noise prediction models is usually restricted to the special area where the meteorological data are available.

All the noise models treat noise as a function of distance, sound power level, different form of attenuations such as geometrical absorptions, barrier effects, ground topography etc. Generally these parameters are measured in the mines and best fitting models are applied to predict noise. Mathematical models are generally complex and cannot be implemented in real time systems. Additionally they fail to predict the future parameters from current and past measurements. It has been seen that noise prediction is a non-stationary process and soft-computing techniques like Fuzzy system, Adaptive network based fuzzy inference system (ANFIS) or (Neuro-Fuzzy), Neural Network etc. have been tested for non-stationary time-series prediction for a long time.

The data assembled through surveys, measurement or knowledge to predict sound pressure level in mines is often imprecise or speculative. Since soft computing methods (fuzzy logic systems, artificial neural network, radial basis network etc )are good tools for prediction of imprecise and uncertainty information, therefore soft computing approach would be the very appropriate technique for modeling the prediction of sound pressure level in opencast mines.

## 5.2 Soft Computing Models for non frequency based noise prediction

In this study, frequency and non-frequency based statistical or mathematical noise prediction models were used to predict opencast mining machineries noise. Hence Soft-Computing models were also applied for both frequency or non-frequency based models. In this section, application of soft computing models for non-frequency based noise prediction model is discussed. Fig 5.1 represents the system diagram for application of soft computing for non-frequency based (VDI-2714) noise prediction model.The following sections represent the application of different types of soft computing models for non-frequency noise prediction models.

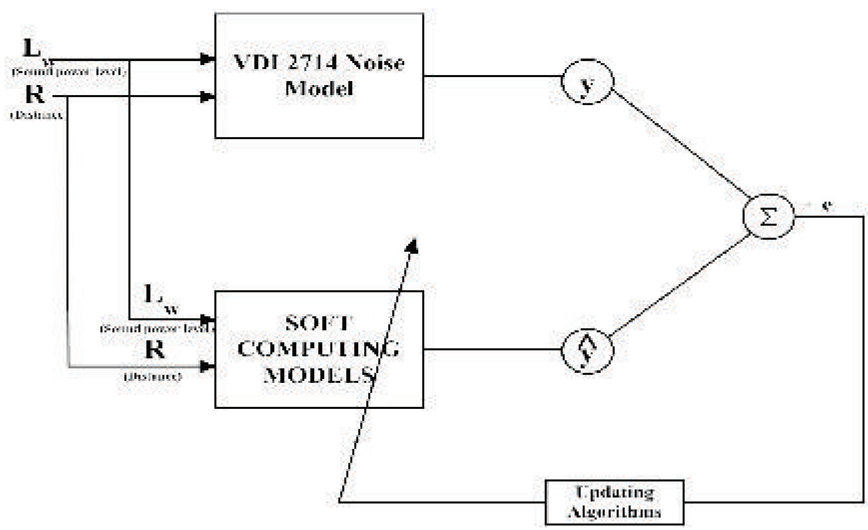



Figure 5.1: Application of Soft Computing for non-frequency based models .

### 5.2.1 Application of Fuzzy Logic Systems for VDI-2714

Mamdani and TSK fuzzy systems were used to predict or estimate the sound pressure level for machineries in an opencast coal mine. With availability of set of measured data as input, the fuzzy system would be able to predict the output for any given input even if a specific input condition has not been covered in the building stage. The given model can be considered as multi input and single output (MISO) model. The methodology for development of fuzzy based sound pressure level prediction model involves the following steps:

1. Selection of input and output variables and Selection of membership function for input and output variables,
2. Formation of linguistic rule base,
3. Defuzzification, and
4. Parameter optimization.

#### 5.2.1.1 Selection of input and output variables and Selection of membership function for input and output variables

The first step in system modeling was the identification of input and output variables called the system's variables. Only those inputs that affect the output to a large extent were selected. The two important input variables were sound power level (SWL) and distance from the source (R). Different forms of fuzzifier have been discussed in Section 4.2.1, Chapter 4. Different fuzzy parameters with their linguistic values for input and output are presented in Table 5.1. For getting better performance, with both the Mamdani and T-S-K fuzzy system, seven membership functions were chosen for SWL and five membership functions were chosen for distance. For this application, triangular and trapezoidal membership functions are used. Figure 5.2(a) and 5.2(b) showed the graphical representation of membership functions of the input parameters. For Mamdani fuzzy system, it was also needed to convert the linguistic values of output to a range of 0 to 1. In the proposed model, for Mamdani Fuzzy system, the output variable had seven membership functions (Table 5.1) and were represented in Figure 5.2(c).

#### 5.2.1.2 Formation of linguistic rule-base

The relationship between input and the output was represented in the from of IF-THEN rules. Let the $1^{st}$ input (Sound power level) be taken as X, the $2^{nd}$ input (Distance from the source) as Y and the output (sound pressure level) be taken as Z. As per the fuzzy systems, both the inputs 'X' and Y had five membership functions. Therefore 25 rules were made. In Mamdani fuzzy model, Max-Min inference was applied. The rules of the Mamdani fuzzy system were generated in the following ways:

$R_1$ : **IF** X is $X_1$ = *"Low"* **AND** Y is $Y_1$ = *"Very Low"* **THEN** sound pressure level(Z) is Z = $Z_1$ = *"Very Low"*;

Table 5.1: Inputs and output with their fuzzy and fuzzy intervals

| Sl.No. | System's linguistic variable | Variables | Linguistic values | Fuzzy interval |
|---|---|---|---|---|
| 1 | Inputs | SWL | Low | 80-100 dBA |
| | | | Medium | 90-110 dBA |
| | | | High | 100-120 dBA |
| | | | Very High | 110-130 dBA |
| | | | Extreme | 120-140 dBA |
| 2 | | Distance | Very Low | 1-10 meter |
| | | | Low | 5-15 meter |
| | | | Medium | 8-20 meter |
| | | | Long | 15-25 meter |
| | | | Very Long | 20-30 meter |
| 3 | Output | SPL | Very Low | 70-80 dBA |
| | | | Low | 80-90 dBA |
| | | | Medium | 85-95 dBA |
| | | | High | 90-100 dBA |
| | | | Very High | 95-105 dBA |
| | | | Extreme | 100-110 dBA |
| | | | Extremely High | 105-115 dBA |

$R_2$ : **IF** X is $X_2$ = *"Medium"* **AND** Y is $Y_2$ = *"Low"* **THEN** sound pressure level(Z) is Z = $Z_2$ = *"Low"*;

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$R_{25}$ : **IF** X is $X_5$ = *"Extreme"* **AND** Y is $Y_5$ = *"Very Long"* **THEN** sound pressure level(Z) is Z = $Z_7$ = *"Extremely High"*;

where $X_1, X_2, \ldots X_5; Y_1, Y_2, \ldots Y_5$ are the linguistic parameters or membership functions of the inputs (X & Y) and $Z_1, Z_2, \ldots Z_7$ are the membership function of output(Z). The generation of rule base in TSK fuzzy system was same as Mamdani fuzzy system. In TSK fuzzy system product inference was applied and the number of rules was 25. The rules were generated in the following ways:

$R_1$ : **IF** X is $X_1$ = *"Low"* **AND** Y is $Y_1$ = *"Very Low"* **THEN**sound pressure level(Z) is Z = $a_1 \times$X + $b_1 \times$ Y + $c_1$ ;

$R_2$ : **IF** X is $X_2$ = *"Medium"* **AND** Y is $Y_2$ =*"Low"* **THEN** sound pressure level(Z) is Z =$a_2 \times$ X + $b_2 \times$ Y + $c_2$ ;

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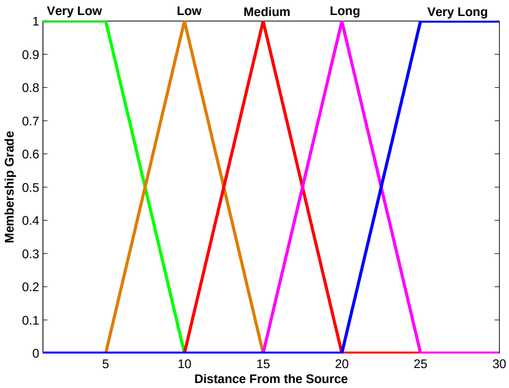
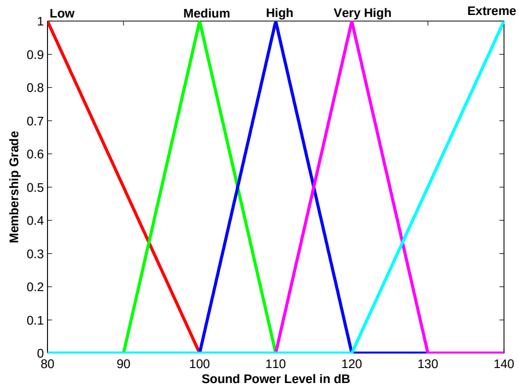
$R_{25}$ : **IF** X is $X_5$ = *"Extreme"* **AND** Y is $Y_5$ = *"Very Long"***THEN** sound pressure level(Z) is Z = $a_{25} \times$ X + $b_{25} \times$ Y + $c_{25}$ ;

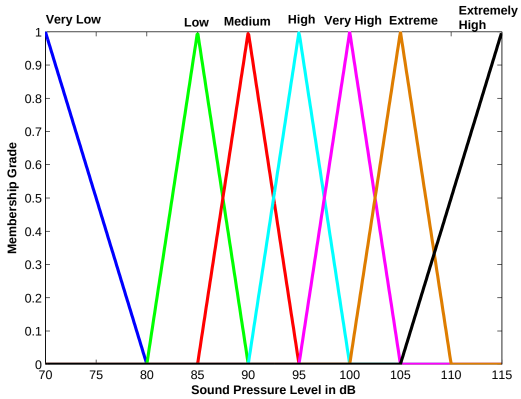
where $a_1, b_1, \ldots a_{25}, b_{25}$ are the coefficients or tune parameters and $c_1, c_2, \ldots c_{25}$ are the bias associated with the output.




(a) Membership function for Distance




(b) Membership function for Sound Power Level




(c) Membership function for Sound Pressure Level

Figure 5.2: Membership function of Inputs and output of Mamdani fuzzy system

#### 5.2.1.3 Defuzzification

In the proposed model, Centroid of area (COA) method of defuzzification is used. The details of defuzzification are already discussed in Section (4.2.4), Chapter 4.

#### 5.2.1.4 Parameter optimization

Following defuzzification process, T-S-K fuzzy system makes prediction the output. The parameters (coefficients) of T-S-K fuzzy system were adjusted ($a_1$, $b_1$, $c_1$. . . $a_{25}$,$b_{25}$, $c_{25}$) repeatedly by trial and error, so that the error could be minimized. The coefficients were fixed when the average error in the whole range of input is below 5 %. This section was only meant for Takagi Sugeno Kang model.

#### 5.2.1.5 Performance study of Mamdani and T-S-K fuzzy system

For calculation of the performance of both the systems, the shovel noise was taken as an example.

Example: for 1 meter distance (input 1), the measured sound pressure level was 102.3 dB (A) i.e. sound power level was120 dB (A) (input 2). It was estimated from VDI-2714 that the predicted SPL was 95.6919 dB by considering all the attenuations. SPL could be determined using the fuzzy models as discussed below:

#### 5.2.1.6 Mamdani fuzzy system

For 1 meter distance, the membership value was 1 i.e. $\mu_{d1}$ ('Low') =1 and for sound power level (swl) of 120 dB, the membership value ($\mu_{swl4}$ ('Very High')) was 1. Mathematical representation of the Mamdani fuzzy system based noise prediction model could be discussed in the following manner (Table 5.2).

Table 5.2: Mathematical representation of Mamdani fuzzy system based noise prediction model

| Rules | Input 1 | Input 2 | Inference Engine | | Defuzzification or Output |
|---|---|---|---|---|---|
| | | | Min | Max | |
| Rule 1 | Distance 1m. $\mu_{d1}$ =1 | SWL 120 dB $\mu_{SWL4}$ =1 | W$_1$=min ($\mu_{d1}$, $\mu_{SWL4})$ $\mu_{min1}$=min(w$_1$, $\mu_{SPL,Low}$)=[0.1, 0.2,. . . ..0.9] | $\mu_{MAX}$= max[$\mu_{min1}$ . . . . . $\mu_{min25}$] | $\sum \frac{\mu_{MAX} \times SPL}{\mu_{MAX}}$ $=\sum_{i=1}^{25} \frac{\mu_z \times z}{\mu_z}$ = 94.9999 dB(A) ≅ 95 dB(A) |
| . | . | . | . | | |
| . | . | . | . | | |
| . | . | . | . | | |
| Rule 25 | $\mu_{d1}$ = 0 | $\mu_{SWL4}$ = 0 | W$_{25}$= min($\mu_{d1}$ , $\mu_{SWL4})$ $\mu_{min25}$=min(w$_{25}$, $\mu_{SPL,High}$)=[0] | | |

The error of the system was found as 0.4789 %. If the error of the system was high, then the output of Mamdani fuzzy system could be improved by increasing the rule base.

#### 5.2.1.7 T-S-K fuzzy system

Mathematical representation of the T-S-K fuzzy system based noise prediction model could be discussed in the following manner (Table 5.3).

The error of the T-S-K system was found to be 0.0380 %. If the error was high, then the output of Sugeno fuzzy system could be emphasized by following the steps:

1. Modification of the tune parameters (a$_1$,b$_1$,C$_1$... a$_{25}$,b$_{25}$,C$_{25}$).

2. Increasing the membership function or increase the rule base.

Due to the functional relation between input and output, the T-S-K fuzzy model was more robust than Mamdani fuzzy system and adaptation was easily done in T-S-K fuzzy system.

Table 5.3: Mathematical representation of T-S-K fuzzy system based noise prediction model

| Rules | Input 1 | Input 2 | Inference Engine | Functional Link of the system | Defuzzification or Output |
|---|---|---|---|---|---|
| | | | Product | | |
| Rule 1 | Distance 1m. $\mu_{d1}=1$ | SWL 120 dB $\mu_{SWL4}=1$ | $W_1 = \mu_{d1} \times \mu_{SWL4} = 1$ | $F_1 = a_1X+b_1Y+C_1 = 1\times 1 + 0.7 \times 120 + 22$ | $\frac{F_1 \times w_1 + F_2 \times w_2 + \ldots F_{25} \times w_{25}}{w_1 + w_2 + \ldots + w_{25}} = \sum_{i=1}^{25} \frac{F_i \times w_i}{w_i} = \sum_{i=1}^{25} \frac{\mu_z \times z}{\mu_z} = 95.8868$ dB A |
| . | . | . | . | . | |
| . | . | . | . | . | |
| . | . | . | . | . | |
| Rule 25 | $\mu_{d1}=0$ | $\mu_{SWL4}=0$ | $W_{25} = \mu_{d1} \times \mu_{SWL4} = 0$ | $F_{25} = a_{25}X+b_{25}Y+C_{25} = 0.5 \times 1 + 0.3 \times 120 + 10$ | |

#### 5.2.1.8 Simulation results and discussion

The proposed system models for noise prediction were validated using simulation studies. The studies were carried out by using MATLAB simulation environment. For validation of the models, the noise data was collected from Balaram opencast coal mine of Mahanadi Coalfields Limited (MCL), Talcher (Orissa, India). The test data was measured using Brüel & Kjaer 2239 (Denmark) precession sound level meter. From the measured parameter, VDI-2714 gives prediction by calculating all the sound attenuations in 'dB (A)' not in octave frequency band. SPL of the different machineries from the above mine was collected. These machineries include Shovel (10m$^3$ bucket capacity), Dozer (410hp), Tipper (10T-160hp), Grader (220 hp) and Dumper (85T).

The fuzzy parameters were suitably chosen to enhance the performance of the designed model. For Mamdani fuzzy inference system (FIS), the number of rules and for T-S-K FIS, the coefficients were the fuzzy parameters. The plot of predicted sound pressure level (SPL) using Mamdani FIS for different values of sound power level (SWL) and distance were plotted in Figure 5.3. The plot shows a complex relationship in the form of a surface. The similar plot for T-S-K fuzzy model was presented in Figure 5.4.

Table 5.4 summarizes the results for noise prediction by proposed models and compares it with standard VDI-2714 noise prediction model for shovel. From the table, it can be seen that the proposed Mamdani and T-S-K models provided average percentage error of 3.9562 and 2.2705 respectively. Similar results for dumper, grader, tipper and dozer were shown in Table 5.5 to 5.8. From the simulation studies, it was observed that the average percentage error of T-S-K fuzzy model was lower than the Mamdani fuzzy model.

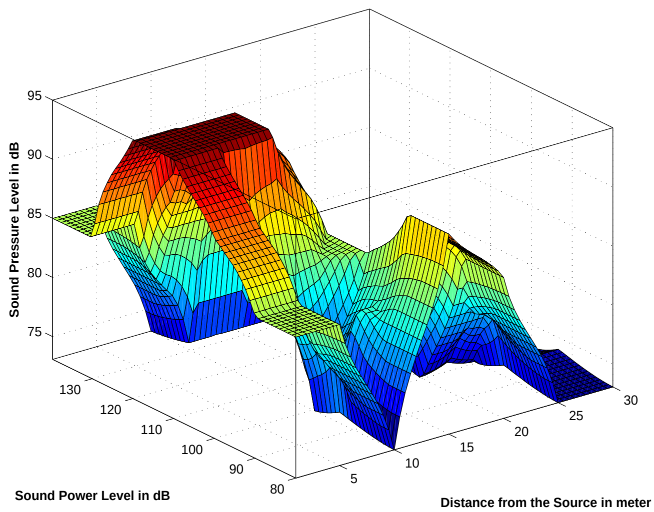



Figure 5.3: Surface plot of Mamdani fuzzy system

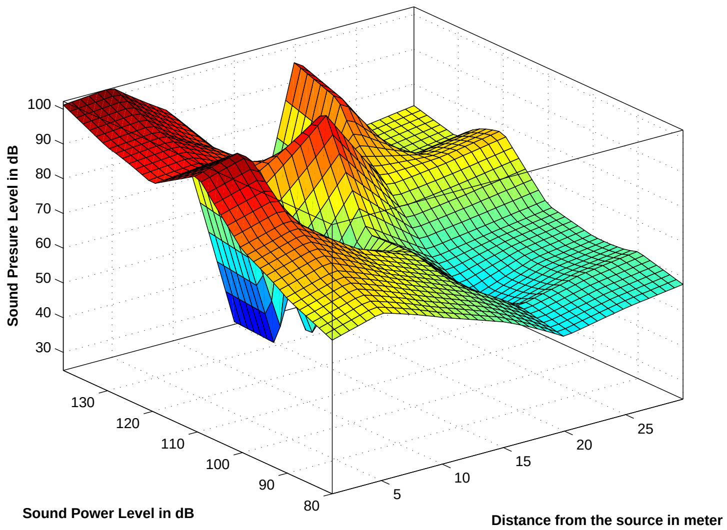



Figure 5.4: Surface plot of T-S-K fuzzy system

### 5.2.2 Application of Neural Network Models in Noise Prediction

In this proposed model, two types of artificial neural networks has been applied to predict mining machinery noise. These include: Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF). Supervised learning methods were applied in both the MLP and RBF system. Iterative based training methods were adopted in both the architectures.

#### 5.2.2.1 Advantages of Artificial Neural Network Models

Some of the advantages of the ANN models are enumerated below:

- Neural networks can provide several advantages over conventional regression models for noise prediction such as VDI-2714, CONCAWE etc. They are claimed to possess the property to learn from a set of data without the need for a full specification of the decision model; they are believed to automatically provide any needed data transformations.

- ANN models are considered to be universal approximator. Here, in this application, MLP and RBF have been used to predict SPL, when parameters like, SWL, distance, wind etc. are given. From the simulation result it was seen that ANN models were able to predict large variety of prediction models with arbitrary accuracy. The results of ISO-9613-2, CONCAWE, ENM, Nordforsk, VDI-2720 models have been presented in this chapter from **Section 5.3.1** to **Section 5.3.3**.

- While using statistical models, the calculation differs from model to model. In ANN based predictor, the structure of the network remains the same. When the network is trained with VDI-2714 data, it behaves like VDI-2714 model. On the other hand when trained with CONCAWE, it behaves like a CONCAWE model. Hence neural network based predictors can predict SPL for variety of models simply by changing the data set.

#### 5.2.2.2 MLP and RBF based Noise Prediction Models:

The ANN based noise prediction models consist of two input constituting sound power level ($x_k$) and distance ($y_k$). The inputs patterns are $x_1(k)$, $x_2(k)$, $x_3(k)$ ... $x_n(k) \in R$, $y_1(k)$, $y_2(k)$, $y_3(k)$ ... $y_n(k)$) and the desired output patterns are: $d_1(k)$, $d_2(k)$, $d_3(k)$ ... $d_n(k) \in R$. During training period the desired network output was calculated with VDI-2714 noise prediction model.

#### 5.2.2.3 Algorithm for training MLP based Noise prediction model

**Step 1**: Select the total number of layers m, the number $n_i$ (i=1,2,..., m -1) of the neurons in each hidden layer and an error tolerance parameter $\varepsilon > 0$.

Table 5.4: Simulation study of Shovel noise

| Distance from the source (meters) | Measured field data (dBA) | Prediction result (dBA) | | | Average percentage error (dBA) | |
|---|---|---|---|---|---|---|
| | | VDI | Mamdani | TSK | Mamdani | TSK |
| 1 | 102.3000 | 95.6919 | 94.9999 | 95.8868 | | |
| 2 | 102.1000 | 95.4828 | 94.9999 | 91.5297 | | |
| 3 | 98.6000 | 91.9738 | 94.9999 | 91.9123 | | |
| 4 | 98.2000 | 91.5648 | 94.0089 | 91.8833 | | |
| 5 | 97.5000 | 90.8559 | 93.0543 | 92.8308 | | |
| 6 | 97.5000 | 90.8469 | 87.9340 | 92.0379 | | |
| 7 | 96.7000 | 90.0380 | 87.3280 | 90.7365 | | |
| 8 | 95.2000 | 88.5291 | 87.6898 | 89.0020 | | |
| 9 | 93.3000 | 86.6202 | 88.8171 | 87.1428 | | |
| 10 | 92.4000 | 85.7113 | 89.7325 | 85.5883 | | |
| 11 | 91.5000 | 84.8025 | 89.6531 | 85.5848 | | |
| 12 | 91.5000 | 84.7937 | 88.7356 | 84.1498 | | |
| 13 | 91.3000 | 84.5848 | 87.7592 | 81.7415 | | |
| 14 | 90.4000 | 83.6760 | 86.8534 | 81.8725 | | |
| 15 | 88.8000 | 82.0672 | 86.2104 | 86.2454 | 3.9562 | 2.2705 |
| 16 | 88.4000 | 81.6585 | 85.5286 | 83.6172 | | |
| 17 | 87.9000 | 81.1497 | 83.2004 | 82.0039 | | |
| 18 | 87.1000 | 80.3410 | 80.8065 | 80.8559 | | |
| 19 | 86.7000 | 79.9323 | 78.3232 | 78.8861 | | |
| 20 | 86.3000 | 79.5236 | 73.9789 | 77.0894 | | |
| 21 | 85.7000 | 78.9149 | 73.4574 | 76.2133 | | |
| 22 | 85.2000 | 78.4063 | 73.6837 | 75.6372 | | |
| 23 | 85.3000 | 78.4976 | 73.7173 | 75.3193 | | |
| 24 | 85.5000 | 78.6890 | 73.6964 | 74.6422 | | |
| 25 | 85.5000 | 78.6804 | 73.7638 | 73.5868 | | |
| 26 | 85.3000 | 78.4718 | 73.7812 | 74.1201 | | |
| 27 | 84.7000 | 77.8632 | 73.7297 | 74.8577 | | |
| 28 | 84.2000 | 77.3547 | 73.6964 | 75.5374 | | |
| 29 | 83.8000 | 76.9461 | 73.6802 | 76.1635 | | |
| 30 | 82.7000 | 75.8376 | 73.5594 | 77.1038 | | |

Table 5.5: Simulation study of Dumper noise

| Distance from the source (meters) | Measured field data (dBA) | Prediction result (dBA) | | | Average percentage error (dBA) | |
|---|---|---|---|---|---|---|
| | | VDI | Mamdani | TSK | Mamdani | TSK |
| 1 | 102.4000 | 95.7919 | 94.9999 | 95.8051 | | |
| 2 | 101.3000 | 94.6828 | 94.9999 | 92.2392 | | |
| 3 | 98.2000 | 91.5738 | 94.9999 | 92.2951 | | |
| 4 | 97.7000 | 91.0648 | 94.4237 | 91.6128 | | |
| 5 | 97.2000 | 90.5559 | 93.2622 | 92.6738 | | |
| 6 | 96.8000 | 90.1469 | 88.8171 | 91.7351 | | |
| 7 | 94.2000 | 87.5380 | 90.2668 | 89.7607 | | |
| 8 | 94.1000 | 87.4291 | 88.8091 | 88.6325 | | |
| 9 | 93.6000 | 86.9202 | 88.4321 | 87.2363 | | |
| 10 | 93.2000 | 86.5113 | 88.6328 | 85.8030 | | |
| 11 | 93.2000 | 86.5025 | 87.5858 | 84.1622 | | |
| 12 | 92.5000 | 85.7937 | 87.6519 | 81.9859 | | |
| 13 | 92.2000 | 85.4848 | 87.0337 | 78.4198 | | |
| 14 | 90.6000 | 83.8760 | 86.6701 | 80.9714 | | |
| 15 | 89.7000 | 82.9672 | 85.2613 | 81.5260 | 3.4807 | 2.4632 |
| 16 | 88.3000 | 81.5585 | 85.5526 | 83.9938 | | |
| 17 | 88.2000 | 81.4497 | 83.2004 | 81.2413 | | |
| 18 | 87.6000 | 80.8410 | 80.8065 | 80.2501 | | |
| 19 | 87.1000 | 80.3323 | 78.4705 | 78.9298 | | |
| 20 | 86.8000 | 80.0236 | 74.0678 | 77.8178 | | |
| 21 | 86.5000 | 79.7149 | 73.6642 | 77.0871 | | |
| 22 | 86.2000 | 79.4063 | 73.6837 | 76.3709 | | |
| 23 | 85.8000 | 78.9976 | 73.7173 | 75.4967 | | |
| 24 | 85.6000 | 78.7890 | 73.7129 | 74.6364 | | |
| 25 | 84.8000 | 77.9804 | 73.6484 | 73.9196 | | |
| 26 | 84.2000 | 77.3718 | 73.6027 | 74.6410 | | |
| 27 | 84.2000 | 77.3632 | 73.6484 | 75.0980 | | |
| 28 | 83.7000 | 76.8547 | 73.6177 | 75.7713 | | |
| 29 | 83.4000 | 76.5461 | 73.6177 | 76.3516 | | |
| 30 | 82.8000 | 75.9376 | 73.5735 | 77.0614 | | |

Table 5.6: Simulation study of Grader noise

| Distance from the source (meters) | Measured field data (dBA) | Prediction result (dBA) | | | Average percentage error (dBA) | |
|---|---|---|---|---|---|---|
| | | VDI | Mamdani | TSK | Mamdani | TSK |
| 1 | 105.3000 | 98.6919 | 94.9998 | 93.4356 | | |
| 2 | 103.4000 | 96.7828 | 94.6926 | 90.8358 | | |
| 3 | 101.2000 | 94.5738 | 93.6257 | 91.8516 | | |
| 4 | 98.7000 | 92.0648 | 93.6257 | 92.1508 | | |
| 5 | 97.2000 | 90.5559 | 93.2622 | 92.6738 | | |
| 6 | 95.5000 | 88.8469 | 90.6732 | 91.1429 | | |
| 7 | 94.3000 | 87.6380 | 90.1149 | 89.8029 | | |
| 8 | 94.1000 | 87.4291 | 88.8091 | 88.6325 | | |
| 9 | 93.7000 | 87.0202 | 88.3061 | 87.2667 | | |
| 10 | 93.2000 | 86.5113 | 88.6328 | 85.8030 | | |
| 11 | 92.6000 | 85.9025 | 88.3354 | 84.7291 | | |
| 12 | 91.8000 | 85.0937 | 88.4174 | 83.5405 | | |
| 13 | 90.4000 | 83.6848 | 88.4416 | 84.6072 | | |
| 14 | 88.6000 | 81.8760 | 88.5144 | 88.8498 | | |
| 15 | 88.5000 | 81.7672 | 86.5253 | 87.6842 | 3.5416 | 2.6519 |
| 16 | 88.2000 | 81.4585 | 85.5758 | 84.3648 | | |
| 17 | 87.9000 | 81.1497 | 83.2004 | 82.0039 | | |
| 18 | 87.3000 | 80.5410 | 80.8065 | 80.6202 | | |
| 19 | 86.5000 | 79.7323 | 78.2566 | 78.8617 | | |
| 20 | 85.8000 | 79.0236 | 73.9001 | 76.3944 | | |
| 21 | 85.4000 | 78.6149 | 73.5058 | 75.9005 | | |
| 22 | 85.1000 | 78.3063 | 73.6837 | 75.5664 | | |
| 23 | 84.6000 | 77.7976 | 73.7173 | 75.0721 | | |
| 24 | 84.2000 | 77.3890 | 73.5058 | 74.6766 | | |
| 25 | 83.8000 | 76.9804 | 73.5058 | 74.3140 | | |
| 26 | 83.2000 | 76.3718 | 73.4690 | 75.0163 | | |
| 27 | 82.9000 | 76.0632 | 73.4690 | 75.6123 | | |
| 28 | 82.5000 | 75.6547 | 73.4574 | 76.2385 | | |
| 29 | 82.1000 | 75.2461 | 73.4461 | 76.8612 | | |
| 30 | 81.8000 | 74.9376 | 73.4461 | 77.4468 | | |

Table 5.7: Simulation study of Tipper noise

| Distance from the source (meters) | Measured field data (dBA) | Prediction result (dBA) | | | Average percentage error (dBA) | |
|---|---|---|---|---|---|---|
| | | VDI | Mamdani | TSK | Mamdani | TSK |
| 1 | 100.9000 | 94.2919 | 94.9999 | 97.0307 | | |
| 2 | 99.7000 | 93.0828 | 94.9999 | 93.6583 | | |
| 3 | 98.6000 | 91.9738 | 94.9999 | 91.9123 | | |
| 4 | 97.5000 | 90.8648 | 94.6008 | 91.5038 | | |
| 5 | 96.5000 | 89.8559 | 93.7718 | 92.3029 | | |
| 6 | 96.2000 | 89.5469 | 89.6281 | 91.4662 | | |
| 7 | 95.8000 | 89.1380 | 88.3193 | 90.4062 | | |
| 8 | 94.8000 | 88.1291 | 88.1080 | 88.8725 | | |
| 9 | 94.3000 | 87.6202 | 87.6099 | 87.4411 | | |
| 10 | 93.7000 | 87.0113 | 87.9268 | 85.9232 | | |
| 11 | 92.8000 | 86.1025 | 88.0890 | 84.5487 | | |
| 12 | 90.6000 | 83.8937 | 89.4570 | 85.7959 | | |
| 13 | 89.5000 | 82.8848 | 89.1651 | 87.0881 | | |
| 14 | 88.4000 | 81.6760 | 88.7072 | 89.5147 | | |
| 15 | 86.8000 | 80.0672 | 88.4074 | 90.7633 | 3.4921 | 3.3099 |
| 16 | 86.2000 | 79.4585 | 85.7905 | 90.7373 | | |
| 17 | 85.8000 | 79.0497 | 83.2004 | 86.4398 | | |
| 18 | 85.2000 | 78.4410 | 80.8065 | 82.7077 | | |
| 19 | 85.2000 | 78.4323 | 77.9947 | 78.6657 | | |
| 20 | 84.7000 | 77.9236 | 73.7645 | 74.9694 | | |
| 21 | 84.5000 | 77.7149 | 73.4139 | 75.0055 | | |
| 22 | 83.8000 | 77.0063 | 73.6837 | 74.6850 | | |
| 23 | 83.5000 | 76.6976 | 73.7173 | 74.6862 | | |
| 24 | 83.5000 | 76.6890 | 73.4350 | 74.6666 | | |
| 25 | 83.2000 | 76.3804 | 73.4352 | 74.5107 | | |
| 26 | 82.8000 | 75.9718 | 73.4247 | 75.1439 | | |
| 27 | 82.6000 | 75.7632 | 73.4352 | 75.7110 | | |
| 28 | 82.2000 | 75.3547 | 73.4247 | 76.3368 | | |
| 29 | 82.2000 | 75.3461 | 73.4574 | 76.8271 | | |
| 30 | 82.2000 | 75.3376 | 73.4932 | 77.3028 | | |

Table 5.8: Simulation study of Dozer noise

| Distance from the source (meters) | Measured field data (dBA) | Prediction result (dBA) | | | Average percentage error (dBA) | |
|---|---|---|---|---|---|---|
| | | VDI | Mamdani | TSK | Mamdani | TSK |
| 1 | 100.5000 | 93.8919 | 94.9999 | 97.3575 | | |
| 2 | 100.2000 | 93.5828 | 94.9999 | 93.2148 | | |
| 3 | 98.2000 | 91.5738 | 94.9999 | 92.2951 | | |
| 4 | 97.5000 | 90.8648 | 94.6008 | 91.5038 | | |
| 5 | 96.7000 | 90.0559 | 93.6217 | 92.4096 | | |
| 6 | 95.4000 | 88.7469 | 90.8220 | 91.0959 | | |
| 7 | 94.8000 | 88.1380 | 89.4250 | 90.0106 | | |
| 8 | 94.2000 | 87.5291 | 88.7007 | 88.6678 | | |
| 9 | 93.6000 | 86.9202 | 88.4321 | 87.2363 | | |
| 10 | 92.5000 | 85.8113 | 89.5960 | 85.6165 | | |
| 11 | 91.8000 | 85.1025 | 89.2974 | 85.3730 | | |
| 12 | 89.6000 | 82.8937 | 90.3719 | 87.3442 | | |
| 13 | 89.3000 | 82.5848 | 89.3400 | 87.5931 | | |
| 14 | 88.8000 | 82.0760 | 88.3243 | 88.1647 | | |
| 15 | 88.2000 | 81.4672 | 86.8423 | 89.0615 | 3.9739 | 2.6800 |
| 16 | 87.9000 | 81.1585 | 85.6396 | 85.4448 | | |
| 17 | 87.4000 | 80.6497 | 83.2004 | 83.1966 | | |
| 18 | 86.6000 | 79.8410 | 80.8065 | 81.4083 | | |
| 19 | 85.5000 | 78.7323 | 77.9947 | 78.7163 | | |
| 20 | 85.5000 | 78.7236 | 73.8578 | 75.9922 | | |
| 21 | 84.8000 | 78.0149 | 73.4352 | 75.2970 | | |
| 22 | 84.3000 | 77.5063 | 73.6837 | 75.0161 | | |
| 23 | 84.2000 | 77.3976 | 73.7173 | 74.9314 | | |
| 24 | 83.8000 | 76.9890 | 73.4574 | 74.6731 | | |
| 25 | 83.5000 | 76.6804 | 73.4690 | 74.4158 | | |
| 26 | 83.5000 | 76.6718 | 73.5058 | 74.9125 | | |
| 27 | 82.8000 | 75.9632 | 73.4574 | 75.6460 | | |
| 28 | 82.5000 | 75.6547 | 73.4574 | 76.2385 | | |
| 29 | 82.4000 | 75.5461 | 73.4809 | 76.7563 | | |
| 30 | 82.4000 | 75.5376 | 73.5188 | 77.2258 | | |

**Step 2**: Randomly select the initial values of the weight vectors $w_{i,j}^m$ , for i=1, 2,... n$_i$ and m=2 (number of layers).

**Step 3**: **Initialization** All the weights $w_{i,j}^m$ were initialized to random number and given as $w_{i,j}^m(0)$

$$w_{i,j}^m \leftarrow w_{i,j}^m(0)$$

**Step 4: Calculation of the neural outputs**

$$\begin{cases} a_{i,j}^m = (w_{i,j}^1)^T \times X_K \\ y_j \ = (w_{i,j}^2)^T \times a_j^m \end{cases}$$

Where $a_{i,j}^m$ was the output of the hidden layer (m=1) and $y_j$ is the output of the output layer. $w_{i,j}^1$ is the weight associated for hidden layer and $w_{i,j}^2$ is the weight associated for output layer. In the model, the weights associated with the hidden layer were basically n$_i$ $\times$ 2 matrix as two inputs were selected and the weight associated with the output layer is 1 $\times$ n$_i$ as this model is a MISO (Multi input and single output) system.

**Step 5: Calculation of the output error** The error was calculated as $e_j = d_j - y_j$. It may be seen that the network produces a scalar output.

**Step 6: Calculation of the derivative of network output of each layer**
**For hidden layer (m=1)**
The derivative of activation function of hidden layer can be represented as

$$\begin{aligned} \dot{f}^1(n^1) &= \frac{d}{dn}\left[\frac{1}{1+\exp^{-n}}\right] = \left[1 - \frac{1}{1+\exp^{-n}}\right]\left[\frac{1}{1+\exp^{-n}}\right] \\ &= (1 - a_{i,j}^m)\,(a_{i,j}^m) \end{aligned}$$

**For output layer (m=2)**
The derivative of activation function of output layer can be represented as

$$\dot{f}^2(n^2) = \frac{d}{dn}(n) = 1$$

Where n is the output of each neuron of the hidden and output layer.

**Step 7: Backpropagation of error by sensitivities at each layer**
Backpropagation of error by sensitivities at each layer was calculated as follows:
**For output layer (m=2)**
$s_j^2 = -2\,\dot{F}^2(n^2)\,(d_j - y_j) = -2\,\dot{f}^2(n^2)\,(e_j)$
**For hidden layer (m=1)**

$$\begin{aligned} s_j^1 &= \dot{F}^1(n^1)(w_{i,j}^2)^T s_j^2 \\ &= \begin{bmatrix} (1-a_{1,j}^1)\,(a_{1,j}^1) & 0 & \cdots & 0 \\ 0 & (1-a_{2,j}^1)\,(a_{2,j}^1) & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & (1-a_{n_i,j}^1)\,(a_{n_i,j}^1) \end{bmatrix} \times\ (w_{i,j}^2)^T s_j^2 \end{aligned}$$

**Step 8: Updating the weight vectors**
The weight matrices are updated next using the following relationship

$$w_{i,j}^2(new) = w_{i,j}^2(old) + \eta\, s_j^2 (a_{i,j}^1)^T$$

$$w_{i,j}^1(new) = w_{i,j}^1(old) + \eta\, s_j^1$$

Where $\eta$ is the momentum parameter or tuning parameter of the system.

**Step 9:** If error $\leq\ \varepsilon$ (0.01) then go to Step 10, otherwise go to Step 3.

**Step 10:** After the learning is completed, the weights were fixed and the network can be used for testing

**Algorithm for RBF based Noise prediction model**

**Step 1**: The centers ($M_i$, i=1, 2, 3,..n) were chosen randomly and updated by applying K-mean clustering algorithm and an error tolerance parameter $\varepsilon$ (0.01) > 0.

This algorithm (K-mean) aims at minimizing an objective function, in this case a squared error function. The objective function was:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} (\|x_i^j - c_j\|^2)$$

where $\|x_i^j - c_j\|^2$is a chosen distance measure between a data point $x_i^{(j)}$and the cluster centre$c_j$, is an indicator of the distance of the $n$ data points from their respective cluster centers.

**Step 2**: Random selection of the initial values of the weight vector $w_{i,j}$ , for i=1, 2,... $M_i$, were chosen.

**Step 3**: **Initialization**

All the weights $w_{i,j}^m$ were initialized to random number and given as $w_{i,j}^m(0)$

$$w_{i,j} \leftarrow w_{i,j}(0)$$

**Step 4: Calculation of the RBFN outputs**

After selecting centers, Gaussian radial functions were used to find the output and that was calculated as follows:

$$y_j = \sum_{j=1}^{k} w_{i,j} \times \phi(\|X_j - C_i\|)$$

Where $y_j$ is the output of RBF model and K is the training samples.

$$u_i = \phi(\|X_j - C_i\|) = \sum_{i=1}^{m} \exp\left(\frac{\|X_j - C_i\|}{2\sigma_i^2}\right)$$

**Step 5: Calculation of the output error**

The error was calculated as follows:

$$E = \sum_{j=1}^{K}(d_j - y_j)^2 = e_j \cong d_j - y_j = d_j - \sum_{j=1}^{K}\sum_{i=1}^{M} w_{i,j} \times \exp\left(\frac{\|X_j - C_i\|}{2\sigma_i^2}\right)$$

Where $d_j$ is the desired output (here sound pressure level) and $y_j$ is the output of

RBF model.

**Step 6: Updating the weight vectors**
The weight matrices are updated next using the following relationship

$$w_{i,j}^{new} = w_{i,j}^{old} + \eta u_i e_j$$

Where $\eta$ is the momentum parameter or tuning parameter of the system.
**Step 7:** If error $\leq \quad \varepsilon$ (0.01) then go to Step 8, otherwise go to Step 3.

**Step 8:** After the learning is complete, the weights were fixed and the network can be used for testing. After training was complete the weights were fixed for testing the model. If the testing results were not perfect, then the training process is continued until the desired performance measure was achieved.

#### 5.2.2.4 Simulation Result and Performance Analysis

To validate the performance of MLP and RBF for SPL prediction, simulation studies were carried out by using MATLAB. A set of 3200 data points were first generated as per the VDI-2714 noise prediction model (Eqn. (4.19)), for this the input parameter were distance and sound power level (SWL). The parameters were varied over the range of 1 to 30 m and 80 to 140 dB (A) respectively. Using these input parameters, SPL was calculated. This data set was the basis for training and evaluating or testing the MLP and RBF prediction models. Out of this set of 3200 points, 3000 were used as training data and 200 were used as testing data. For MLP, Back propagation (BP) algorithm was used for training the network. In RBF, the centers were trained using K-mean clustering and weights were trained using LMS algorithm. The spread parameter was set as per the equation 4.21 ( Section 4.4.2,Chapter 4). The root mean square error (RMSE) was used as the performance index, it was calculated as

$$\begin{aligned} RMSE &= \sqrt{\frac{\sum_{i=1}^{N}(VDI_i - Estimated_i)^2}{N}} \\ RMSE_{(dB)} &= 20\,\log_{10}(RMSE) \end{aligned} \tag{5.1}$$

The performance of MLP network is discussed first. A three layer MLP was used for the SPL prediction. The input layer consists of model input i.e. SWL and distance. The output layer consists of only one node representing the SPL. The log-sigmoid activation was used in hidden layer and linear activation function was used in output layer. The number of neurons in the hidden layer was varied between 2 to 10 and the performance of the network was determined. The results obtained are presented in Table 5.9. The first column of the Table 5.9 represented the number of hidden nodes in the MLP network;

the second column represented the RMSE of the network during the training period. Considering the model, the output of the VDI-2714 model was scaled between 0 to 1. The error was calculated as per the equation 5.1. Since the output of the MLP is in the form of an absolute quantity, the SPL calculated from VDI-2714 model was scaled. The highest value of output (VDI-2714) was 1 and remaining SPL value was scaled with this value. The slope of the linear activation function was adjusted, so that the maximum output of the MLP model is 1. Fig. 5.5 represented the performance of MLP model for 100 testing samples. The performance of predicting the SPL using MLP by varying the number of nodes is presented in Fig.5.6 where, it can be seen that a MLP with five hidden nodes provides the best performance.

Table 5.9: Comparison of RMS Errors from Different MLP Network Topologies

| **Description of MLP network topology** | **Training set RMS Error (3000 samples) in dB** | **Testing set RMS Error (200 samples) in dB** |
|---|---|---|
| 1 hidden layer, 2 nodes | 8.9333 | 9.5174 |
| 1 hidden layer, 4 nodes | 8.0614 | 8.5886 |
| 1 hidden layer, 5 nodes | 7.7322 | 8.2511 |
| 1 hidden layer, 6 nodes | 10.4705 | 10.5981 |
| 1 hidden layer, 10 nodes | 20.6594 | 20.5794 |

The RBF network was similar to the MLP system. The structure of RBF system has an input layer, hidden layer with centers and one node in output layer. The number of centers in the hidden layer was varied from 5 to 500 and the performance of the network was determined. Gaussian basis function was used in hidden layer, for which the centers were determined by K-mean clustering. The results were obtained and presented in Table 5.10. The first column of the Table 5.10 represents the number of centers; the second column represented the RMSE of the network during training period. For proper comparison, the output of the VDI model was scaled between 0 to 1. The error was calculated as similar to MLP model. Figure 5.7 represented the performance of RBF model for 100 testing samples. The performance of RBF against number of centers is presented in Fig.5.8. From this figure it can be seen that a RBF network with sixty centers provide the best performance.

Further the the performance of both the prediction models for small number of training samples were investigated. The number of training samples was varied and the performances of both networks were investigated. Following the prediction of the proposed models using VDI-2714 model, a realistic implication for SPL prediction was considered. For the machineries e.g. Shovel (10m$^3$ bucket capacity), Dozer (410hp), Tipper (10T-160hp), Grader (220 hp) and Dumper (85T) were selected to predict the sound pressure level (SPL). The validation data was collected from Balaram opencast coal mines, Mahanadi Coalfield Limited (MCL), Talcher (Orissa, India). The test data or the field data was measured using Bruel & Kjaer 2236. The experimental data were collected for these

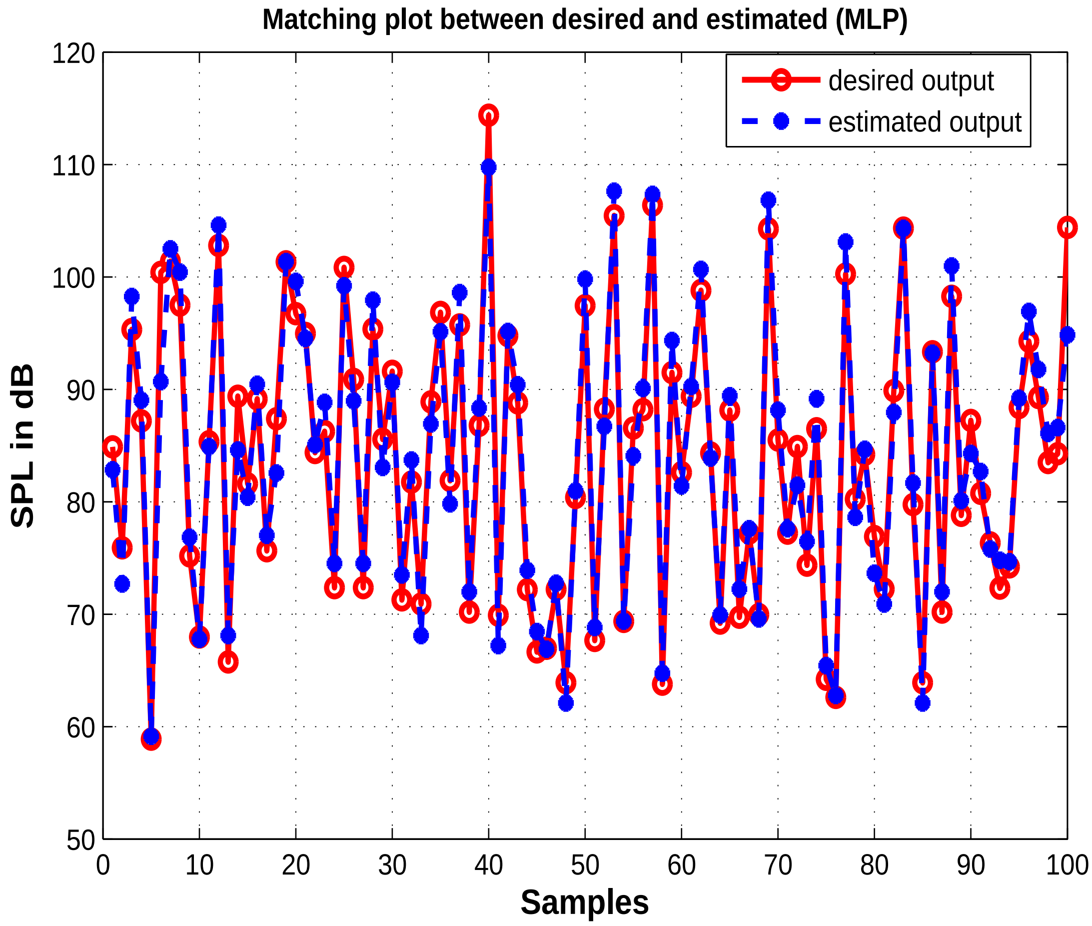
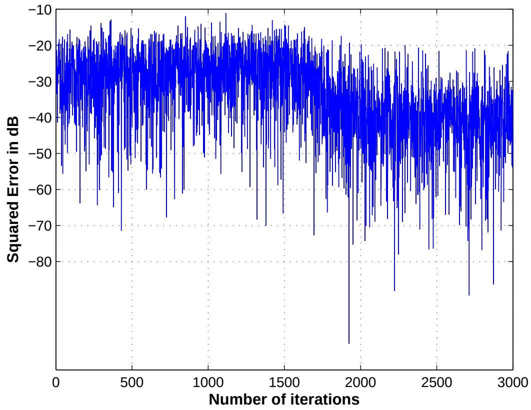


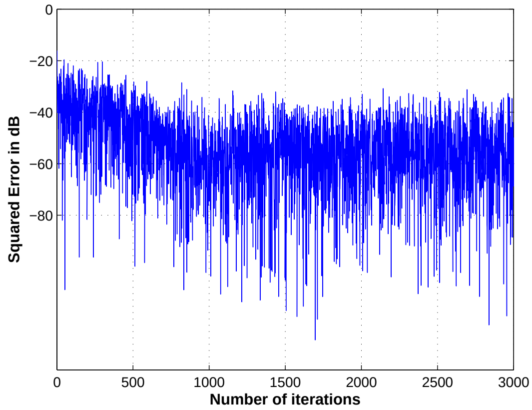

Figure 5.5: Prediction performance of MLP network for 100 samples.

machineries in the range of distance (1 to 30 meter) and SWL (80 to 140 dB (A)). The MLP and RBF weights were frozen on completion of the experiment in first part. SPL was predicted using MLP and RBF for each of these machineries and was compared with the VDI-2714 model. The results are presented in Table 5.11 to 5.13 and also represented graphically in Fig.5.9. It may be noted that the performance of RBF model is much better than the performance of MLP model (considering average percentage error as performance index).

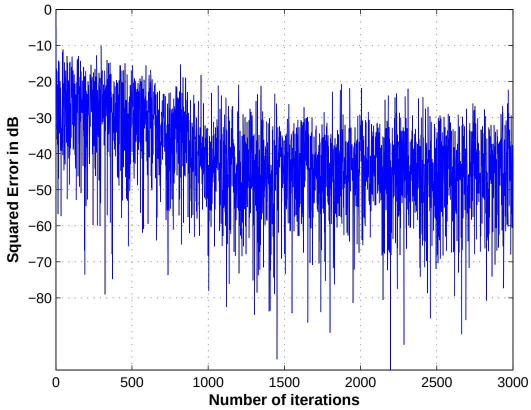
The performance of the proposed models was investigated when number of training samples was less. Table 5.14 represented the performance of RBF and MLP systems with different training samples varying from 3000 to 500. After training, the weights of both the models were fixed to test the performance of the models. For finding the performance of these models, shovel noise was taken as an example. Fig 5.10 represents the performance of best RBF system (sixty centers) at different training and testing samples for shovel noise prediction. In this figure, the performance of the RBF model ( sixty centers) which was trained with 3000 to 500 training samples were compared with



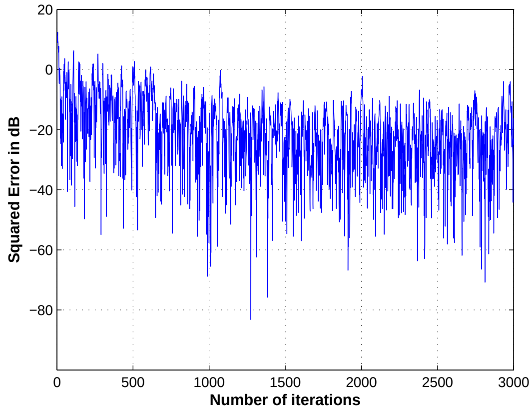

(a) 1 hidden layer with 2 nodes




(b) 1 hidden layer with 4 nodes




(c) 1 hidden layer with 5 nodes




(d) 1 hidden layer with 10 nodes

Figure 5.6: Square error (in dB) of Multi Layer Perceptron (MLP) with different hidden nodes

the best MLP network (five hidden node) which was trained with only 3000 samples. The comparisons were based on shovel noise prediction. It was clear from Fig.5.10 that the performance of RBF system with smaller set of training samples (500 training samples) was better than the best MLP architecture (5 hidden nodes). Similarly, representation for MLP system was shown in Fig 5.11. It was observed that the performance of MLP system with less training samples was not better than the RBF system.

RBF uses sixty centers where as MLP uses five hidden nodes. Hence computational complexity of RBF is much higher than MLP. The summary of computational complexity has been presented in Table 5.15. From this it can be inferred that RBF provides better performance but its computational complexity is approximately 1.65 times higher (as considering CPU time as performance index).

Table 5.10: Comparison of RMS Errors from Different Radial Basis Function Network Topologies

| Description of radial basis function network topology | Training set RMS Error (3000 samples) in dB | Testing set RMS Error (200 samples) in dB |
|---|---|---|
| 1 hidden layer, 5 centers | 13.9646 | 14.8898 |
| 1 hidden layer, 10 centers | 6.2237 | 8.1991 |
| 1 hidden layer, 20 centers | 3.4346 | 9.3171 |
| 1 hidden layer, 30 centers | 4.4462 | 8.0317 |
| 1 hidden layer, 40 centers | 4.9614 | 8.5504 |
| 1 hidden layer, 50 centers | 4.8771 | 7.0430 |
| 1 hidden layer, 60 centers | 0.4531 | 2.1226 |
| 1 hidden layer, 70 centers | 2.0752 | 2.4048 |
| 1 hidden layer, 80 centers | 1.3948 | 2.8905 |
| 1 hidden layer, 90 centers | 3.7877 | 2.4798 |
| 1 hidden layer, 100 centers | 3.0436 | 2.5578 |
| 1 hidden layer, 500 centers | 6.4361 | 2.1794 |

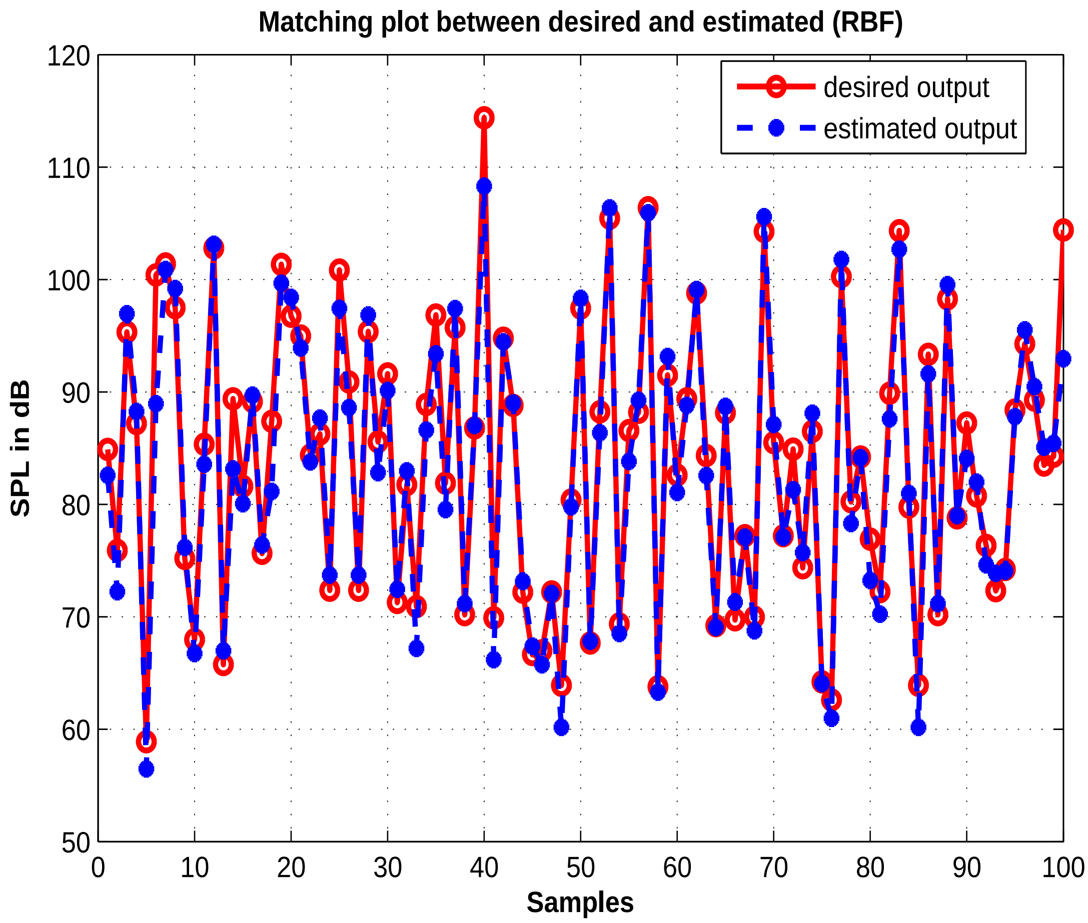
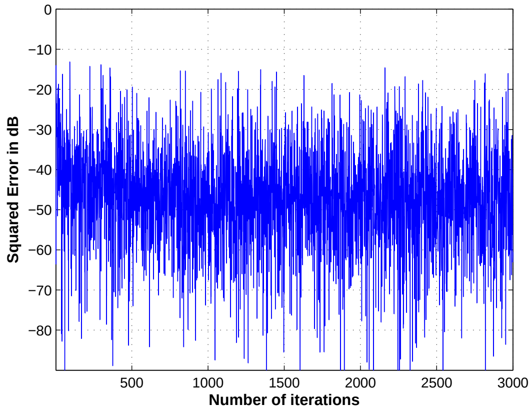
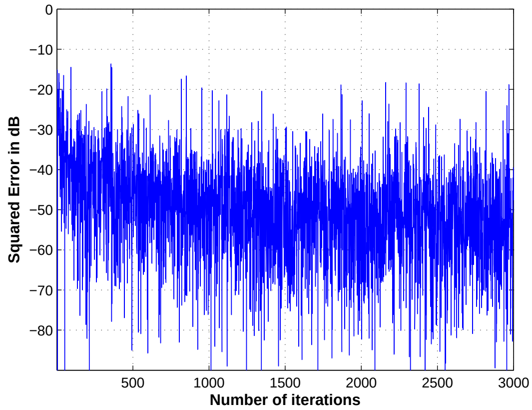


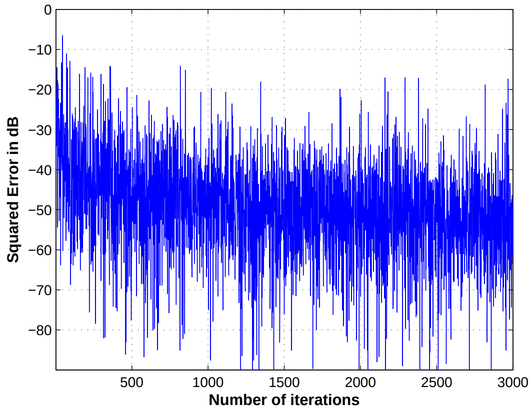

Figure 5.7: Prediction performance of RBF network for 100 samples.



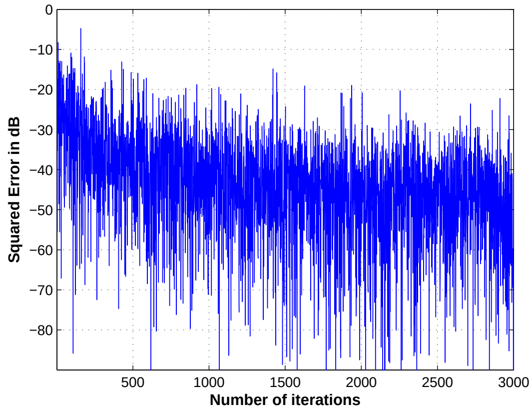

(a) 20 Centers




(b) 60 Centers




(c) 100 Centers




(d) 500 Centers

Figure 5.8: Square error (in dB) of Radial Basis Function Network (RBF) with different centers

Table 5.11: Simulation Study of Shovel and Dumper Noise

| Distance from the source (meters) | **Shovel Noise** | | | | **Dumper Noise** | | | |
|---|---|---|---|---|---|---|---|---|
| | Measured field data (dBA) | Prediction result (dBA) | | | Measured field data (dBA) | Prediction result (dBA) | | |
| | | VDI-2714 | RBF | MLP | | VDI-2714 | RBF | MLP |
| 1 | 102.3 | 95.6919 | 92.3078 | 85.7903 | 102.4 | 95.7919 | 92.3633 | 85.8940 |
| 2 | 102.1 | 95.4828 | 95.5873 | 90.9482 | 101.3 | 94.6828 | 94.4882 | 90.1167 |
| 3 | 98.6 | 91.9738 | 93.7972 | 90.0823 | 98.2 | 91.5738 | 93.1882 | 89.6666 |
| 4 | 98.2 | 91.5648 | 94.3546 | 91.3763 | 97.7 | 91.0648 | 93.9011 | 90.8573 |
| 5 | 97.5 | 90.8559 | 93.1299 | 91.7783 | 97.2 | 90.5559 | 92.9960 | 91.4673 |
| 6 | 97.5 | 90.8469 | 91.5242 | 92.5402 | 96.8 | 90.1469 | 91.4121 | 91.8153 |
| 7 | 96.7 | 90.0380 | 89.9430 | 92.2228 | 94.2 | 87.5380 | 88.7933 | 89.6314 |
| 8 | 95.2 | 88.5291 | 88.5802 | 90.9979 | 94.1 | 87.4291 | 87.9761 | 89.8576 |
| 9 | 93.3 | 86.6202 | 87.1077 | 89.2192 | 93.6 | 86.9202 | 87.3386 | 89.5301 |
| 10 | 92.4 | 85.7113 | 86.4361 | 88.3689 | 93.2 | 86.5113 | 87.0544 | 89.1976 |
| 11 | 91.5 | 84.8025 | 85.7208 | 87.4323 | 93.2 | 86.5025 | 86.8859 | 89.1920 |
| 12 | 91.5 | 84.7937 | 85.3878 | 87.3558 | 92.5 | 85.7937 | 86.0047 | 88.3902 |
| 13 | 91.3 | 84.5848 | 84.5221 | 87.0131 | 92.2 | 85.4848 | 85.1403 | 87.9432 |
| 14 | 90.4 | 83.6760 | 83.1573 | 85.8987 | 90.6 | 83.8760 | 83.3071 | 86.1048 |
| 15 | 88.8 | 82.0672 | 81.4089 | 84.0265 | 89.7 | 82.9672 | 82.1316 | 84.9504 |
| 16 | 88.4 | 81.6585 | 80.8275 | 83.3544 | 88.3 | 81.5585 | 80.7406 | 83.2522 |
| 17 | 87.9 | 81.1497 | 80.3713 | 82.5508 | 88.2 | 81.4497 | 80.6614 | 82.8567 |
| 18 | 87.1 | 80.3410 | 79.7126 | 81.4186 | 87.6 | 80.8410 | 80.2182 | 81.9259 |
| 19 | 86.7 | 79.9323 | 79.4773 | 80.6724 | 87.1 | 80.3323 | 79.8922 | 81.0765 |
| 20 | 86.3 | 79.5236 | 79.2419 | 79.9085 | 86.8 | 80.0236 | 79.7563 | 80.4114 |
| 21 | 85.7 | 78.9149 | 78.7721 | 78.9300 | 86.5 | 79.7149 | 79.5527 | 79.7304 |
| 22 | 85.2 | 78.4063 | 78.3322 | 78.0408 | 86.2 | 79.4063 | 79.2455 | 79.0358 |
| 23 | 85.3 | 78.4976 | 78.3340 | 77.7354 | 85.8 | 78.9976 | 78.7625 | 78.2306 |
| 24 | 85.5 | 78.6890 | 78.3527 | 77.5159 | 85.6 | 78.7890 | 78.4349 | 77.6146 |
| 25 | 85.5 | 78.6804 | 78.2682 | 77.0882 | 84.8 | 77.9804 | 77.6857 | 76.4021 |
| 26 | 85.3 | 78.4718 | 78.1564 | 76.4558 | 84.2 | 77.3718 | 77.2048 | 75.3855 |
| 27 | 84.7 | 77.8632 | 77.7931 | 75.4297 | 84.2 | 77.3632 | 77.3386 | 74.9467 |
| 28 | 84.2 | 77.3547 | 77.5051 | 74.5013 | 83.7 | 76.8547 | 77.0091 | 74.0227 |
| 29 | 83.8 | 76.9461 | 77.1810 | 73.6694 | 83.4 | 76.5461 | 76.7363 | 73.2898 |
| 30 | 82.7 | 75.8376 | 75.7551 | 72.1815 | 82.8 | 75.9376 | 75.8772 | 72.2751 |
| Average percentage error (dBA) | | | **0.7664** | **2.5193** | | | **0.8212** | **2.5213** |

Table 5.12: Simulation Study of Grader and Tipper Noise

| Distance from the source (meters) | **Grader Noise** | | | | **Tipper Noise** | | | |
|---|---|---|---|---|---|---|---|---|
| | Measured field data (dBA) | Prediction result (dBA) | | | Measured field data (dBA) | Prediction result (dBA) | | |
| | | VDI-2714 | RBF | MLP | | VDI-2714 | RBF | MLP |
| 1 | 105.3 | 98.6919 | 94.0268 | 88.9065 | 100.9 | 94.2919 | 91.2754 | 84.3419 |
| 2 | 103.4 | 96.7828 | 96.9975 | 92.2982 | 99.7 | 93.0828 | 92.2709 | 88.4532 |
| 3 | 101.2 | 94.5738 | 96.3909 | 92.7810 | 98.6 | 91.9738 | 93.7972 | 90.0823 |
| 4 | 98.7 | 92.0648 | 94.6979 | 91.8950 | 97.5 | 90.8648 | 93.6886 | 90.6496 |
| 5 | 97.2 | 90.5559 | 92.9960 | 91.4673 | 96.5 | 89.8559 | 92.5382 | 90.7410 |
| 6 | 95.5 | 88.8469 | 90.8301 | 90.4672 | 96.2 | 89.5469 | 91.2174 | 91.1933 |
| 7 | 94.3 | 87.6380 | 88.8770 | 89.7352 | 95.8 | 89.1380 | 89.7181 | 91.2906 |
| 8 | 94.1 | 87.4291 | 87.9761 | 89.8576 | 94.8 | 88.1291 | 88.3980 | 90.5833 |
| 9 | 93.7 | 87.0202 | 87.4095 | 89.6338 | 94.3 | 87.6202 | 87.7763 | 90.2556 |
| 10 | 93.2 | 86.5113 | 87.0544 | 89.1976 | 93.7 | 87.0113 | 87.3530 | 89.7156 |
| 11 | 92.6 | 85.9025 | 86.5454 | 88.5707 | 92.8 | 86.1025 | 86.6658 | 88.7778 |
| 12 | 91.8 | 85.0937 | 85.5836 | 87.6660 | 90.6 | 83.8937 | 84.7092 | 86.4260 |
| 13 | 90.4 | 83.6848 | 83.9103 | 86.0842 | 89.5 | 82.8848 | 83.2216 | 85.1568 |
| 14 | 88.6 | 81.8760 | 81.2510 | 84.0477 | 88.4 | 81.6760 | 81.6390 | 83.8426 |
| 15 | 88.5 | 81.7672 | 81.1717 | 83.7191 | 86.8 | 80.0672 | 79.7086 | 81.9832 |
| 16 | 88.2 | 81.4585 | 80.6541 | 83.1500 | 86.2 | 79.4585 | 78.8924 | 81.1147 |
| 17 | 87.9 | 81.1497 | 80.3713 | 82.5508 | 85.8 | 79.0497 | 78.4450 | 80.4209 |
| 18 | 87.3 | 80.5410 | 79.9121 | 81.6213 | 85.2 | 78.4410 | 77.9348 | 79.5020 |
| 19 | 86.5 | 79.7323 | 79.2756 | 80.4707 | 85.2 | 78.4323 | 78.0403 | 79.1646 |
| 20 | 85.8 | 79.0236 | 78.7479 | 79.4069 | 84.7 | 77.9236 | 77.7211 | 78.3086 |
| 21 | 85.4 | 78.6149 | 78.4872 | 78.6308 | 84.5 | 77.7149 | 77.6518 | 77.7366 |
| 22 | 85.1 | 78.3063 | 78.2408 | 77.9417 | 83.8 | 77.0063 | 77.0382 | 76.6588 |
| 23 | 84.6 | 77.7976 | 77.7167 | 77.0447 | 83.5 | 76.6976 | 76.6790 | 75.9663 |
| 24 | 84.2 | 77.3890 | 77.2371 | 76.2393 | 83.5 | 76.6890 | 76.5699 | 75.5568 |
| 25 | 83.8 | 76.9804 | 76.8027 | 75.4281 | 83.2 | 76.3804 | 76.2186 | 74.8473 |
| 26 | 83.2 | 76.3718 | 76.2767 | 74.4206 | 82.8 | 75.9718 | 75.8755 | 74.0369 |
| 27 | 82.9 | 76.0632 | 76.1047 | 73.7001 | 82.6 | 75.7632 | 75.8018 | 73.4144 |
| 28 | 82.5 | 75.6547 | 75.7844 | 72.8826 | 82.2 | 75.3547 | 75.4690 | 72.5995 |
| 29 | 82.1 | 75.2461 | 75.2927 | 72.0656 | 82.2 | 75.3461 | 75.4032 | 72.1593 |
| 30 | 81.8 | 74.9376 | 74.6891 | 71.3431 | 82.2 | 75.3376 | 75.1552 | 72.2751 |
| Average percentage error (dBA) | | | **0.8676** | **2.4878** | | | **0.7369** | **2.5284** |

Table 5.13: Simulation Study of Dozer Noise

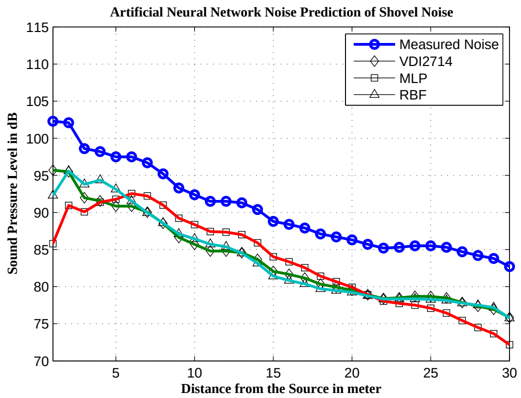
| Distance from the source (meters) | Dozer Noise | | | |
|---|---|---|---|---|
| | Measured field data (dBA) | Prediction result (dBA) | | |
| | | VDI-2714 | RBF | MLP |
| 1 | 100.5 | 93.8919 | 90.8870 | 83.9290 |
| 2 | 100.2 | 93.5828 | 92.9206 | 88.9730 |
| 3 | 98.2 | 91.5738 | 93.1882 | 89.6666 |
| 4 | 97.5 | 90.8648 | 93.6886 | 90.6496 |
| 5 | 96.7 | 90.0559 | 92.6908 | 90.9486 |
| 6 | 95.4 | 88.7469 | 90.7589 | 90.3635 |
| 7 | 94.8 | 88.1380 | 89.2404 | 90.2538 |
| 8 | 94.2 | 87.5291 | 88.0452 | 89.9613 |
| 9 | 93.6 | 86.9202 | 87.3386 | 89.5301 |
| 10 | 92.5 | 85.8113 | 86.5237 | 88.4725 |
| 11 | 91.8 | 85.1025 | 85.9760 | 87.7427 |
| 12 | 89.6 | 82.8937 | 83.7450 | 85.3945 |
| 13 | 89.3 | 82.5848 | 83.0509 | 84.9510 |
| 14 | 88.8 | 82.0760 | 81.9665 | 84.2529 |
| 15 | 88.2 | 81.4672 | 80.9320 | 83.4120 |
| 16 | 87.9 | 81.1585 | 80.3964 | 82.8437 |
| 17 | 87.4 | 80.6497 | 79.9024 | 82.0419 |
| 18 | 86.6 | 79.8410 | 79.2278 | 80.9124 |
| 19 | 85.5 | 78.7323 | 78.3156 | 79.4651 |
| 20 | 85.5 | 78.7236 | 78.4604 | 79.1067 |
| 21 | 84.8 | 78.0149 | 77.9274 | 78.0341 |
| 22 | 84.3 | 77.5063 | 77.5048 | 77.1508 |
| 23 | 84.2 | 77.3976 | 77.3501 | 76.6516 |
| 24 | 83.8 | 76.9890 | 76.8629 | 75.8488 |
| 25 | 83.5 | 76.6804 | 76.5165 | 75.1374 |
| 26 | 83.5 | 76.6718 | 76.5658 | 74.7093 |
| 27 | 82.8 | 75.9632 | 76.0046 | 73.6048 |
| 28 | 82.5 | 75.6547 | 75.7844 | 72.8826 |
| 29 | 82.4 | 75.5461 | 75.6248 | 72.3468 |
| 30 | 82.4 | 75.5376 | 75.3929 | 71.9012 |
| Average percentage error (dBA) | | | **0.8414** | **2.5285** |

Table 5.14: Performance of RBF and MLP based Models at Different Training Samples

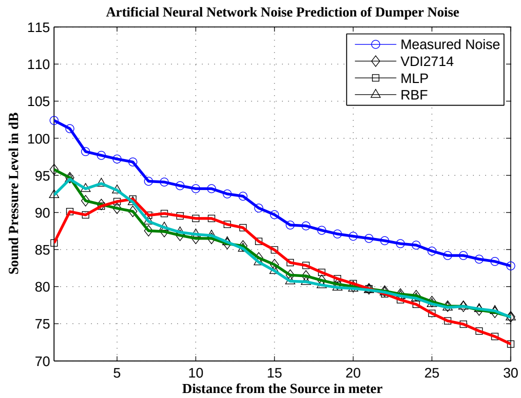
| Number of Training Samples | Number of Testing Samples | RMSE (dB) of MLP Networks | RMSE (dB) of RBF Networks |
|---|---|---|---|
| 3000 | 200 | 7.7322 | 0.4531 |
| 2000 | 1200 | 9.5615 | 1.0479 |
| 1000 | 2200 | 9.7839 | 4.47706 |
| 500 | 2700 | 24.5037 | 7.2205 |

Table 5.15: Complexity Analysis of RBF and MLP Noise Prediction Model

| **Complexity Analysis** | **RBF (2-60-1)** | **MLP (2-5-1)** |
|---|---|---|
| Multiplication / Division | 120 | 15 |
| Addition / Subtraction | 60 | 15 |
| Exponential | 60 | 5 |
| CPU-time (in sec) | 7.2660 | 3.8120 |




(a)

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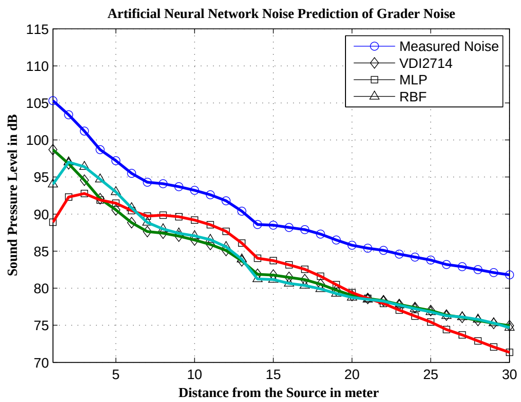


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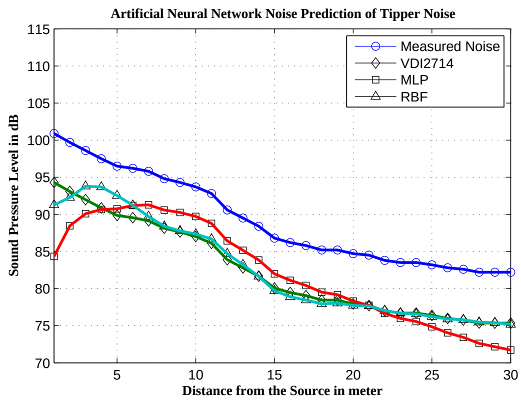
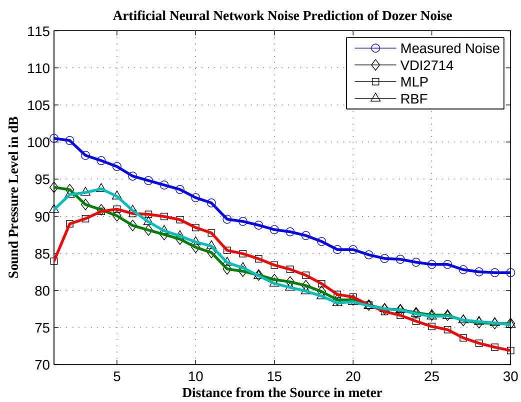



(d)




(e)

Figure 5.9: Artificial neural network noise prediction for different machineries in the study area

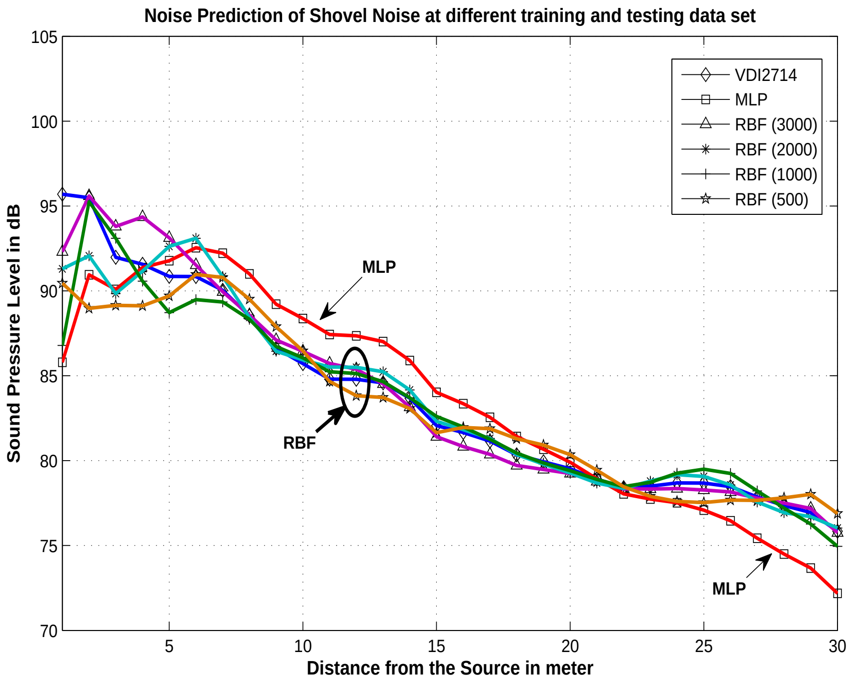



Figure 5.10: Performance of RBF noise prediction model with different training data set for shovel noise prediction

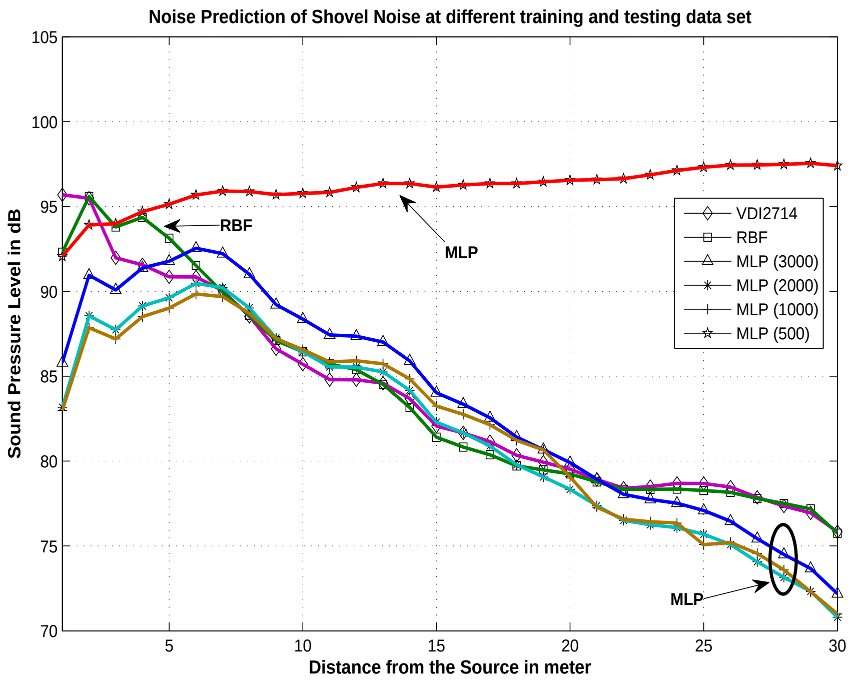



Figure 5.11: Performance of MLP noise prediction model with different training data set for shovel noise prediction

### 5.2.3 Application of Adaptive Network based Fuzzy Inference System (ANFIS) for Machinery Noise Prediction

In this present study, an attempt has been made to use adaptive fuzzy model (ANFIS) or Neuro-Fuzzy model to predict sound pressure level by using sound power level and distance as input parameters. This study is similar to Mamdani and T-S-K fuzzy application as discussed in previous section. According to Fig. 5.1, the soft computing model is ANFIS and LMS based updating algorithm is adopted. The system architecture of the adaptive fuzzy system based prediction model is analyzed and represented in Fig. 5.12. The methodology for the development of the adaptive fuzzy noise prediction model involves the following steps:

1. Selection of input and output variables;
2. Selection of membership functions;
3. Formation of linguistic rule base;
4. Defuzzification and
5. Training of parameters of the fuzzy model.

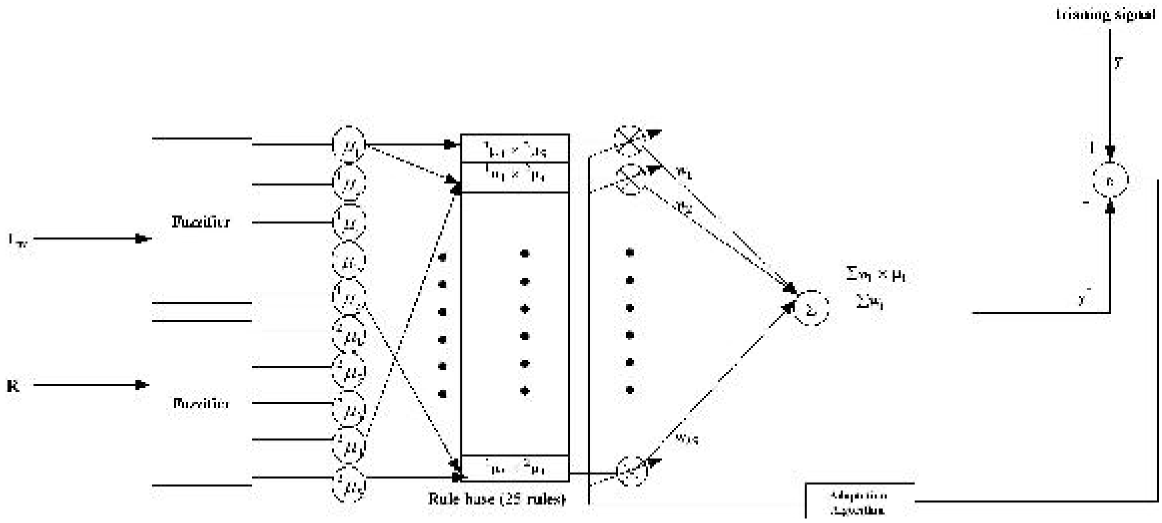


Figure 5.12: Adaptive fuzzy system architecture for noise prediction

In the proposed model ( Fig. 5.12), the two inputs are sound power level ($L_W$) and distance from the source (R) respectively. Each input has five membership functions e.g. $L_W^{(1)}, L_W^{(2)}...L_W^{(5)}$ corresponding to ($L_W$) and $R^{(1)}, R^{(2)}...R^{(5)}$ for R. The process of fuzzification of input ($L_W$) and R is done with triangular membership function. The membership functions are represented as "$L_W^{(1)} = low\ (80 - 100\ dB)$","$L_W^{(2)} = medium\ (90 -$

110 $dB$)"..."$L_W^{(5)} = veryhigh$ (120 − 140 $dB$)" for the input $L_W$. The membership functions corresponding to this input variables are $\mu_{L_1}, \mu_{L_2}, ...\mu_{L_5}$. Similarly the membership functions for R are represented as "$R^{(1)}$ = *medium low*(0 − 10 *meter*)","$R^{(2)}$ = *low* (1 − 15 *meter*)"..."$R^{(5)}$ = *high* (20 − 30 *meter*)" for the input R and the membership corresponding to these input variables are $\mu_{R_1}, \mu_{R_2}, ...\mu_{R_5}$ respectively. Graphical representation of membership function of input parameters(($L_W$) and R) was depicted in Fig. 5.2(a) and (b) in earlier as discussed in section 5.2.1.

#### 5.2.3.1 Formation of linguistic rule-base for ANFIS system

The relationship between input and the output are represented in the from of IF-THEN rules. The membership function $L_W^{(1)}, L_W^{(2)}...L_W^{(5)}$ and $R^{(1)}, R^{(2)}...R^{(5)}$ are the inputs to the rule-base. Let the output, Sound pressure level is expressed as Z. Since there are two inputs and each input has five possible fuzzy sets. The system can have at most $5^2$ =25 rules. In the proposed model, product inference was considered. Each of these rules receive the membership from each of input variable fuzzy sets. Hence rules are formed in following manner;

$R_1$ : **IF** $L_W$ *is* $L_W^{(1)}$ **AND**$R$ *is* $R^{(1)}$ **THEN** sound pressure level (Z)
is Z = $(\mu_{L_1}(L_W^{(1)})\times\mu_{R_1}(R^{(1)})\times w_1;$

$R_2$ : **IF** $L_W$ *is* $L_W^{(1)}$ **AND**$R$ *is* $R^{(2)}$ **THEN** sound pressure level (Z)
is Z = $(\mu_{L_1}(L_W^{(1)})\times\mu_{R_2}(R^{(2)})\times w_2;$

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$R_{25}$ : **IF** $L_W$ *is* $L_W^{(5)}$ **AND**$R$ *is* $R^{(5)}$ **THEN** sound pressure level (Z)
is Z = $(\mu_{L_5}(L_W^{(5)})\times\mu_{R_5}(R^{(5)})\times w_{25};$

Since the system has 25 rules, each rule is associated with a weight. The rules $R_1, R_2...R_{25}$ are associated with weights $(w_1, w_2...w_{25})$ respectively. These weights are initialized to random values at the beginning. Since this model was structured with product inference engine, therefore the fuzzy system can be considered as Takagi-Sugeno-Kang (TSK) fuzzy system.

#### 5.2.3.2 Defuzzification

In general ANFIS structure is similar to T-S-K fuzzy model. Hence Centroid of area (COA) method of defuzzification has been used for determining the output. The estimated output is determined as

$$\hat{y} = \frac{\sum_{i=1}^{25} w_i \times \psi_i}{\sum_{i=1}^{25} w_i} \tag{5.2}$$

where $\psi_i = \mu_{Lk} \times \mu_{Rm}$. where k = 1,..5 , m = 1,..5 corresponding to number of fuzzy sets in $L_w$ and R.

#### 5.2.3.3 Training of parameters of the fuzzy model.

In the model presented at Fig. 5.12, weights $w_i, (i = 1, 2, ...25)$ are unknown. These are initialized to random values at the beginning. Subsequently these weights are updated using LMS algorithm which was first proposed by Widrow and McCool in 1976 [211]. This is similar to the adaption used by Patra and Mulgrew [169]. The weights can be updated iteratively by;

$$e(k) = y(k) - \hat{y}(k) \tag{5.3}$$

$$W(k+1) = W(k) + 2\alpha e(k)\psi(k) \tag{5.4}$$

Where k is the time index, W(k+1)refers to the new weights of the system and W(k) is the existing weight. W=$[(w_1, w_2...w_{25})]^T$ is the weight vector and $\psi = [(\psi_1, \psi_2...\psi_{25})]$ is the output of the inference engine.

#### 5.2.3.4 Simulation Result and Discussion

The proposed model is simulated using MATLAB software. The flowchart for the ANFIS system is shown in Fig.5.13.

The training data set was derived from the VDI-2714 noise prediction model (Eq.(3.3)). A set of 3200 data set was generated for different values of input parameters $L_W$ and R.Using these data in VDI-2714 model SPL was determined. This constituted y for training . The fuzzy network was trained with 3000 sets out of the total data generated. Remaining 200 data set was used for testing the model. The performance of training was validated using mean square error(MSE) as performance index. The efficiency and simplicity of the fuzzy system was validated using the CPU time. Fig.5.14 shows the error update curve during training of the system. Fig.5.15 shows the performance of the system with 200 samples and it was observed that the mean square error for prediction is 2.73 %. The adaptive fuzzy algorithm took CPU time of 0.0625 sec approximately as compared to 0.5 sec for the VDI-2714 model.

To test the stability of the model, validation data is essential. The validation data is collected from Balaram Opencast coal mines, Mahanadi Coalfield Limited (MCL), Talcher (Orissa, India). The test data or the field data was measured using Bruel & Kjaer 2236 (Denmark) sound level meter. From the measured parameter, VDI-2714 gives prediction

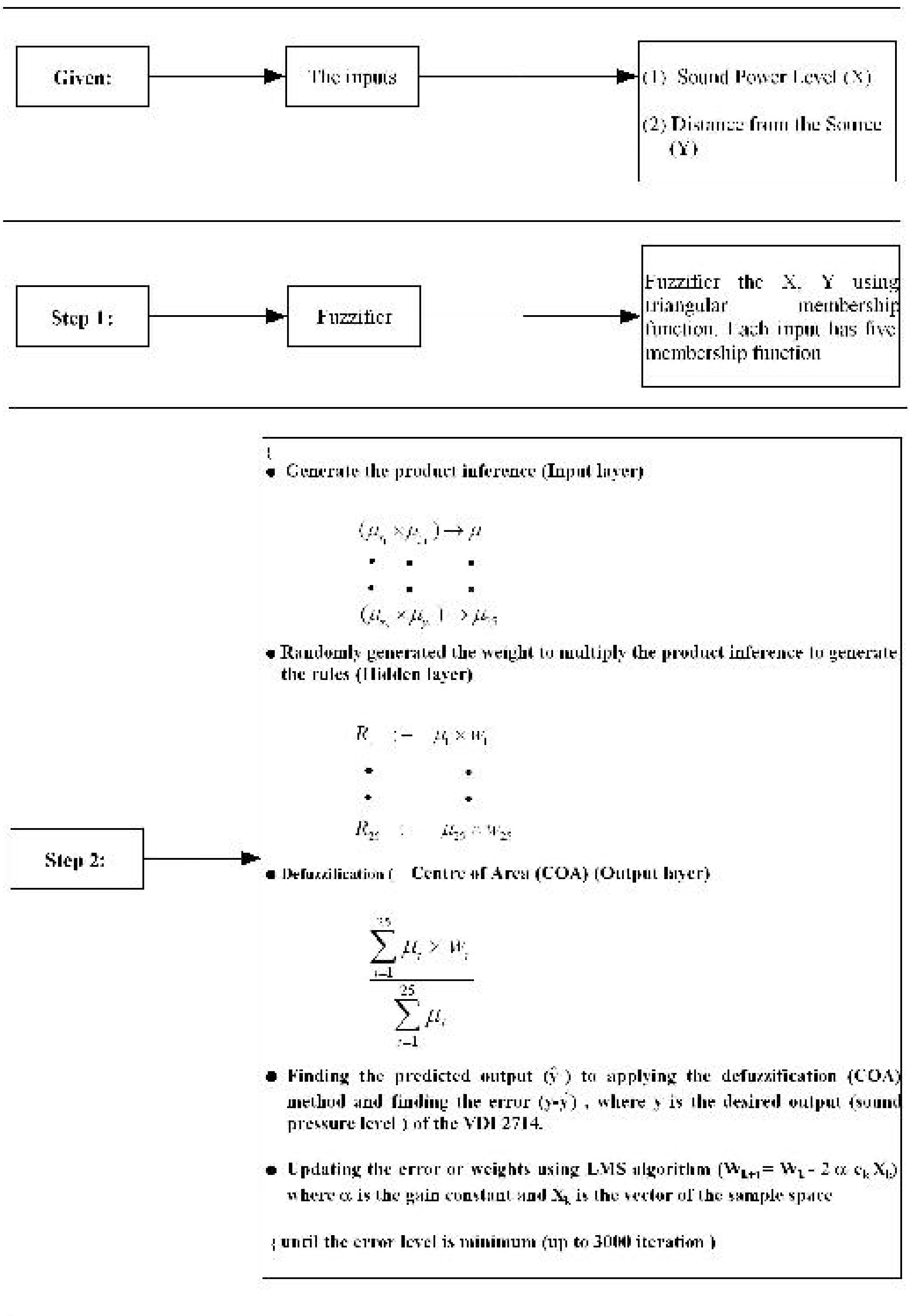



Figure 5.13: Flowchart of the adaptive fuzzy noise prediction model

by calculating all the sound attenuations in 'dB (A)' not in octave frequency band. In general, numerous machineries are used in opencast mines for production, so it is difficult to show the noise prediction of all the machineries using the proposed model here. The machineries ex. Shovel ($10m^3$ bucket capacity), Dozer (410HP), Tipper (10T-160HP), Grader (220 HP) and Dumper (85T) were selected to predict the sound pressure level (SPL) by using VDI2714 and adaptive fuzzy system. Prediction results of the two models (VDI-2714 and ANFIS) for Dozer machine were graphically represented in Fig. 5.16 (a). These models were compared by using measured distance (R) and sound power level (SWL). The prediction results were also represented in Table 5.16. Similar plot for other machineries were represented in Figs. 5.16 (b), (c), (d) and (e) respectively. Table 5.16 shows the measured field data (validation data) and prediction results of the two models (VDI-2714 and ANFIS) of all the selected machineries. It is seen that the ANFIS noise prediction model closely matches with VDI-2714 model results in noise prediction.

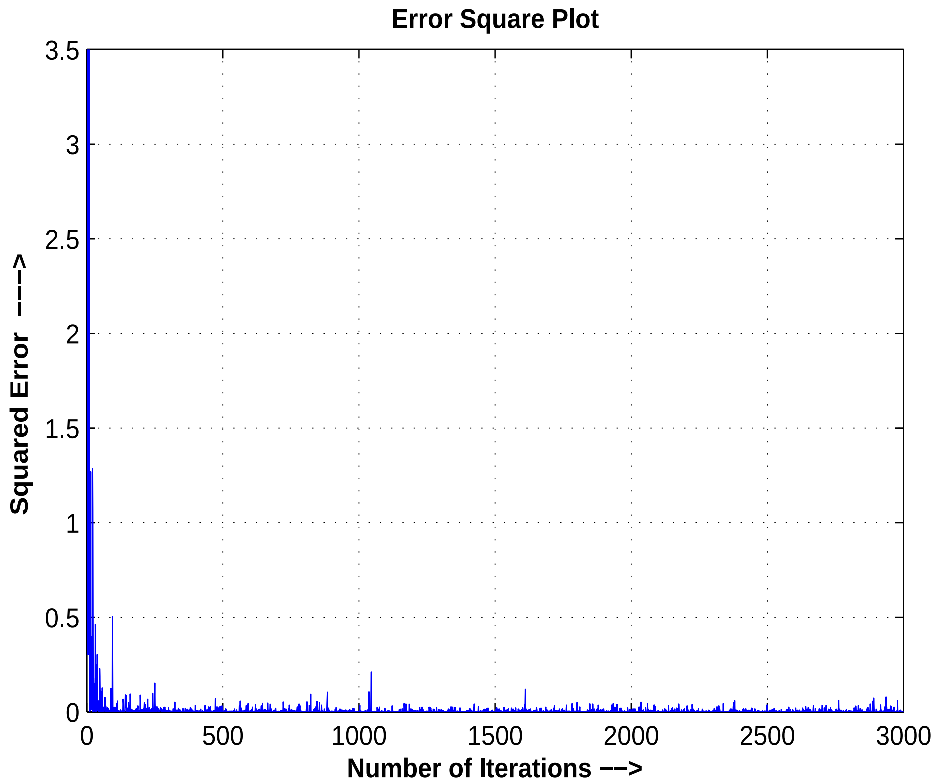



Figure 5.14: Square error of the adaptive fuzzy system

#### 5.2.3.5 Advantages of neuro-fuzzy model

From the present research study, it is found that the Neuro-Fuzzy or ANFIS model takes 0.0625 sec CPU time vis-a-vis 0.5 sec CPU time for VDI-2714 noise prediction model. Some of the advantages of the model are enumerated below:

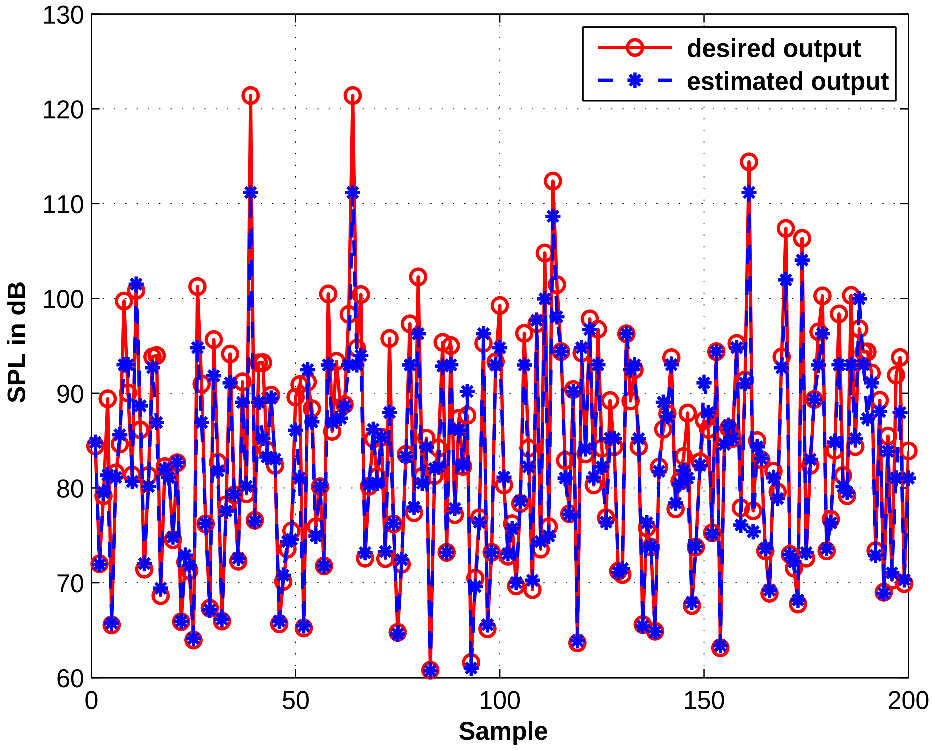
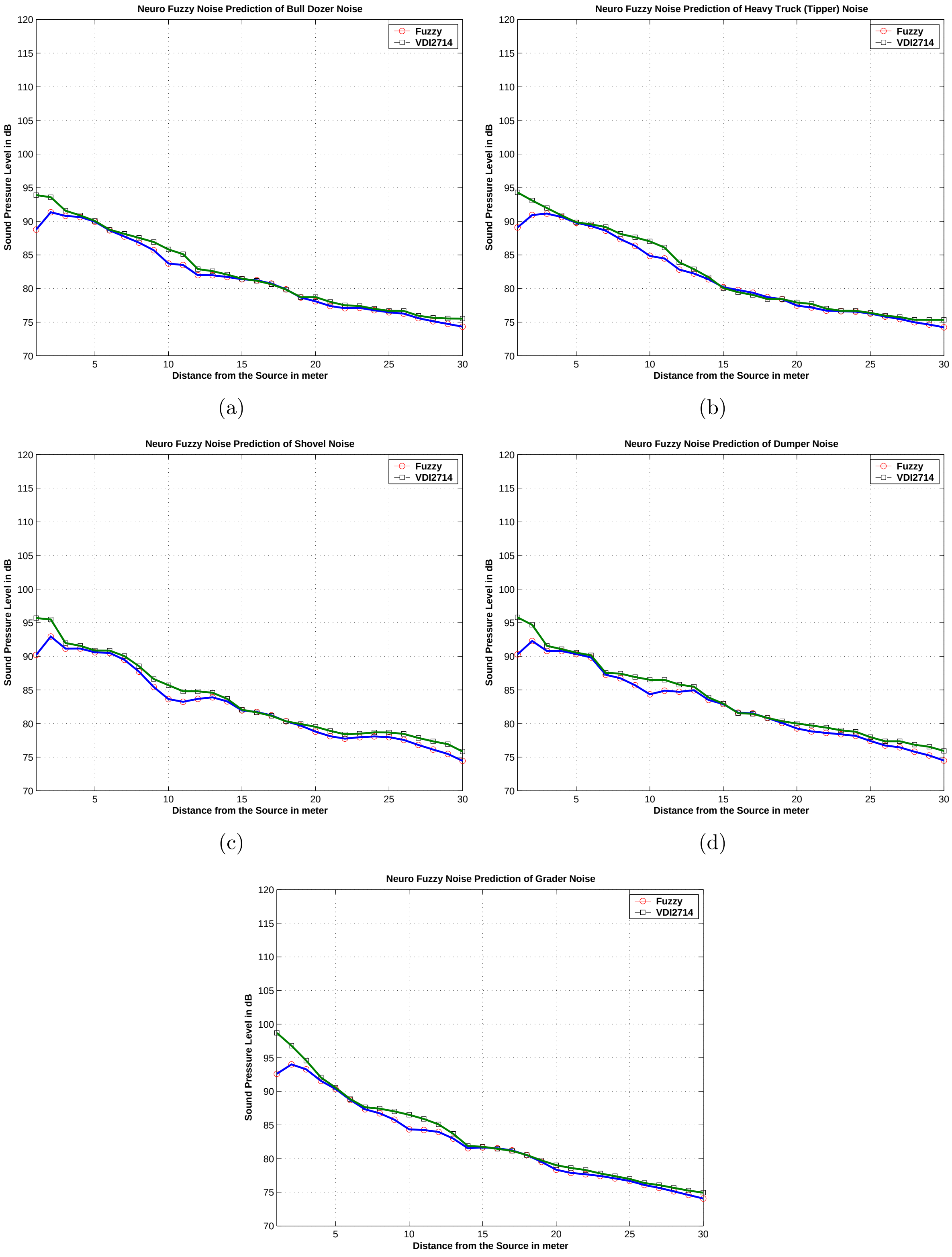



Figure 5.15: Prediction performance of adaptive fuzzy system (ANFIS)for 200 samples

- The noise generated from industrial machineries is generally represented by mathematical models. One such model is VDI-2714 . In this model, the input parameters are distance (R) and sound power level (SWL ($L_W$)); the model predicts the sound pressure level (SPL ($L_P$)). Sound pressure level (SPL) was determined for each set of measured distance (R) and Sound power level (SWL). The process has to be repeated for each machinery. The calculation was complex. The fuzzy models need to be trained once for any specific machinery. Once the fuzzy model was trained, SPL can be determined for any input condition. The model predicts SPL with very little CPU time (12%) compared to VDI-2714. In general, the network can be trained to work for any standard model. The prediction would correspond to the model for which it was trained.

- The model of ANFIS remains fixed as long as input and output remain the same. This can be implemented as a fixed hardware. The training data is based on actual measurement. This information can be used to train the network. Hence same network with different training sets can provide approximate result for different mines/working conditions.

- ANFIS model can be built using DSP hardware available in market. This can be




(a) (b) (c) (d) (e)

Figure 5.16: ANFIS noise prediction for machineries in the study area

used in instrument for measurement owing to low CPU time. Higher CPU time of VDI2714 model will prohibit its usage in portable instrument.

- The ANFIS model can be used to predict noise of machineries for other models also. This can be done by using a different training data sheet. In an instrument, this can be implemented easily, where the instrument can provide prediction for different models.

## 5.3 Soft Computing Models for Frequency based Noise Prediction

For validation of the models (Frequency dependent soft computing based noise prediction models), the noise data was collected from Panchpatmali Bauxite Mine, (NALCO), Damanjodi (Koraput, Odisha, India).The test data was measured using Brüel & Kjaer 2236 (Denmark) precision sound level meter. From the measured parameter, ISO-9613-2 gives prediction by calculating all the sound attenuations. SPL of the different machineries from the above mine was collected. These machineries include Dozer (416 hp), Shovel ($3m^3$ bucket capacity, 320 hp), Pay-Loader (555hp), Dumper (50T), Rock-breaker (120 hp), Rotary Percussive Drill (324 hp), Double Roll Toothed Crusher. The experimental data were collected for these machineries in the range of distance (5 to 150 m) , SWL (100 to 140 dB (A)), wind speed (2-7 m/sec), relative humidity(55-62%) and temperature (28-$32^0$C). The detailed input parameters used for frequency based noise models are represented in Table 5.17.

### 5.3.1 Application of Fuzzy Logic System for Frequency based Noise Prediction

In the present study, an attempt has been made to use fuzzy system to predict or estimate the sound pressure level of machineries used in an opencast bauxite mine. With availability of set of measured data input and output of the fuzzy system, it would be able to predict the output for any given input even if a specific input condition had not been covered in the building stage. The given model was a MISO (Multi Input and Single Output) model. All the procedure for Mamdani and T-S-K fuzzy system is same as per VDI-2714 and discussed earlier. The input and output selection for both fuzzy system was represented as follows:

#### 5.3.1.1 Selection of input and output variables

The first step in system modeling was the identification of input and output variables called the system's variables. Only those inputs that affected the output to a large

Table 5.16: ANFIS noise prediction for different machineries

| Distance From the Source in meter | Shovel Noise in dB | | | Dumper Noise in dB | | | Grader Noise in dB | | | Tipper Noise in dB | | | Dozer Noise in dB | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Measured field data (dBA) | Prediction result (dBA) | | Measured field data (dBA) | Prediction result (dBA) | | Measured field data (dBA) | Prediction result (dBA) | | Measured field data (dBA) | Prediction result (dBA) | | Measured field data (dBA) | Prediction result (dBA) | |
| | | N-Fuzzy | VDI | | N-Fuzzy | VDI | | N-Fuzzy | VDI | | N-Fuzzy | VDI | | N-Fuzzy | VDI |
| 1 | 102.3000 | 90.2051 | 95.6919 | 102.4000 | 90.2853 | 95.7919 | 105.3000 | 92.6115 | 98.6919 | 100.9000 | 89.0821 | 94.2919 | 100.5000 | 88.7612 | 93.8919 |
| 2 | 102.1000 | 92.9455 | 95.4828 | 101.3000 | 92.2722 | 94.6828 | 103.4000 | 94.0081 | 96.7828 | 99.7000 | 90.9254 | 93.0828 | 100.2000 | 91.3463 | 93.5828 |
| 3 | 98.6000 | 91.1476 | 91.9738 | 98.2000 | 90.7961 | 91.5738 | 101.2000 | 93.2710 | 94.5738 | 98.6000 | 91.1476 | 91.9738 | 98.2000 | 90.7961 | 91.5738 |
| 4 | 98.2000 | 91.1557 | 91.5648 | 97.7000 | 90.7761 | 91.0648 | 98.7000 | 91.5560 | 92.0648 | 97.5000 | 90.6297 | 90.8648 | 97.5000 | 90.6297 | 90.8648 |
| 5 | 97.5000 | 90.5989 | 90.8559 | 97.2000 | 90.3440 | 90.5559 | 97.2000 | 90.3440 | 90.5559 | 96.5000 | 89.7812 | 89.8559 | 96.7000 | 89.9376 | 90.0559 |
| 6 | 97.5000 | 90.5077 | 90.8469 | 96.8000 | 89.8325 | 90.1469 | 95.5000 | 88.7188 | 88.8469 | 96.2000 | 89.2976 | 89.5469 | 95.4000 | 88.6398 | 88.7469 |
| 7 | 96.7000 | 89.4805 | 90.0380 | 94.2000 | 87.2589 | 87.5380 | 94.3000 | 87.3358 | 87.6380 | 95.8000 | 88.6022 | 89.1380 | 94.8000 | 87.7336 | 88.1380 |
| 8 | 95.2000 | 87.7212 | 88.5291 | 94.1000 | 86.7376 | 87.4291 | 94.1000 | 86.7376 | 87.4291 | 94.8000 | 87.3480 | 88.1291 | 94.2000 | 86.8217 | 87.5291 |
| 9 | 93.3000 | 85.4354 | 86.6202 | 93.6000 | 85.6965 | 86.9202 | 93.7000 | 85.7857 | 87.0202 | 94.3000 | 86.3448 | 87.6202 | 93.6000 | 85.6965 | 86.9202 |
| 10 | 92.4000 | 83.6372 | 85.7113 | 93.2000 | 84.3542 | 86.5113 | 93.2000 | 84.3542 | 86.5113 | 93.7000 | 84.8404 | 87.0113 | 92.5000 | 83.7230 | 85.8113 |
| 11 | 91.5000 | 83.2331 | 84.8025 | 93.2000 | 84.8830 | 86.5025 | 92.6000 | 84.2596 | 85.9025 | 92.8000 | 84.4620 | 86.1025 | 91.8000 | 83.4994 | 85.1025 |
| 12 | 91.5000 | 83.6705 | 84.7937 | 92.5000 | 84.7308 | 85.7937 | 91.8000 | 83.9743 | 85.0937 | 90.6000 | 82.8242 | 83.8937 | 89.6000 | 81.9843 | 82.8937 |
| 13 | 91.3000 | 83.9048 | 84.5848 | 92.2000 | 84.9497 | 85.4848 | 90.4000 | 82.9754 | 83.6848 | 89.5000 | 82.2313 | 82.8848 | 89.3000 | 81.9700 | 82.5848 |
| 14 | 90.4000 | 83.2946 | 83.6760 | 90.6000 | 83.5142 | 83.8760 | 88.6000 | 81.5435 | 81.8760 | 88.4000 | 81.3709 | 81.6760 | 88.8000 | 81.7200 | 82.0760 |
| 15 | 88.8000 | 81.9558 | 82.0672 | 89.7000 | 82.8950 | 82.9672 | 88.5000 | 81.6649 | 81.7672 | 86.8000 | 80.1925 | 80.0672 | 88.2000 | 81.3840 | 81.4672 |
| 16 | 88.4000 | 81.7271 | 81.6585 | 88.3000 | 81.6275 | 81.5585 | 88.2000 | 81.5292 | 81.4585 | 86.2000 | 79.7832 | 79.4585 | 87.9000 | 81.2411 | 81.1585 |
| 17 | 87.9000 | 81.2228 | 81.1497 | 88.2000 | 81.5252 | 81.4497 | 87.9000 | 81.2228 | 81.1497 | 85.8000 | 79.3791 | 79.0497 | 87.4000 | 80.7425 | 80.6497 |
| 18 | 87.1000 | 80.3335 | 80.3410 | 87.6000 | 80.8185 | 80.8410 | 87.3000 | 80.5240 | 80.5410 | 85.2000 | 78.7269 | 78.4410 | 86.6000 | 79.8765 | 79.8410 |
| 19 | 86.7000 | 79.7007 | 79.9323 | 87.1000 | 80.0842 | 80.3323 | 86.5000 | 79.5157 | 79.7323 | 85.2000 | 78.4125 | 78.4323 | 85.5000 | 78.6528 | 78.7323 |
| 20 | 86.3000 | 78.7986 | 79.5236 | 86.8000 | 79.2704 | 80.0236 | 85.8000 | 78.3542 | 79.0236 | 84.7000 | 77.4620 | 77.9236 | 85.5000 | 78.0998 | 78.7236 |
| 21 | 85.7000 | 78.1231 | 78.9149 | 86.5000 | 78.8310 | 79.7149 | 85.4000 | 77.8747 | 78.6149 | 84.5000 | 77.1786 | 77.7149 | 84.8000 | 77.4028 | 78.0149 |
| 22 | 85.2000 | 77.7547 | 78.4063 | 86.2000 | 78.6088 | 79.4063 | 85.1000 | 77.6748 | 78.3063 | 83.8000 | 76.7150 | 77.0063 | 84.3000 | 77.0677 | 77.5063 |
| 23 | 85.3000 | 77.9729 | 78.4976 | 85.8000 | 78.4024 | 78.9976 | 84.6000 | 77.4136 | 77.7976 | 83.5000 | 76.6210 | 76.6976 | 84.2000 | 77.1139 | 77.3976 |
| 24 | 85.5000 | 78.0839 | 78.6890 | 85.6000 | 78.1699 | 78.7890 | 84.2000 | 77.0572 | 77.3890 | 83.5000 | 76.5662 | 76.6890 | 83.8000 | 76.7719 | 76.9890 |
| 25 | 85.5000 | 77.9792 | 78.6804 | 84.8000 | 77.4094 | 77.9804 | 83.8000 | 76.6758 | 76.9804 | 83.2000 | 76.2752 | 76.3804 | 83.5000 | 76.4721 | 76.6804 |
| 26 | 85.3000 | 77.5712 | 78.4718 | 84.2000 | 76.7400 | 77.3718 | 83.2000 | 76.0750 | 76.3718 | 82.8000 | 75.8299 | 75.9718 | 83.5000 | 76.2664 | 76.6718 |
| 27 | 84.7000 | 76.8183 | 77.8632 | 84.2000 | 76.4671 | 77.3632 | 82.9000 | 75.6479 | 76.0632 | 82.6000 | 75.4758 | 75.7632 | 82.8000 | 75.5899 | 75.9632 |
| 28 | 84.2000 | 76.1314 | 77.3547 | 83.7000 | 75.8165 | 76.8547 | 82.5000 | 75.1337 | 75.6547 | 82.2000 | 74.9773 | 75.3547 | 82.5000 | 75.1337 | 75.6547 |
| 29 | 83.8000 | 75.4846 | 76.9461 | 83.4000 | 75.2580 | 76.5461 | 82.1000 | 74.5923 | 75.2461 | 82.2000 | 74.6400 | 75.3461 | 82.4000 | 74.7371 | 75.5461 |
| 30 | 82.7000 | 74.4604 | 75.8376 | 82.8000 | 74.5073 | 75.9376 | 81.8000 | 74.0617 | 74.9376 | 82.2000 | 74.2338 | 75.3376 | 82.4000 | 74.3228 | 75.5376 |
| Mean Square error | 0.9738 | | | 0.9512 | | | 0.9167 | | | 0.8236 | | | 0.8597 | | |

Table 5.17: The input parameters with possible range for frequency based noise prediction model.

| Input parameters | Possible ranges for frequency based noise prediction model |
|---|---|
| Distance | 5 to 150 meter |
| Sound power level (SWL) | 100 to 140 dB (A) |
| Wind speed | 2-7 m/sec |
| Relative humidity | 55-62 % |
| Temperature | 28-32$^0$C |

extent were selected. The five important input variables were sound power level (SWL), distance, wind speed, temperature and relative humidity. Inclusion of more number of inputs to the system requires more number of rules and hence the complexity increases. The universe of discourse was also decided on the basis of the physical nature of the problem. In the selection procedure, the above mentioned inputs and the output were taken in the form of linguistic format which displayed an important role in the application of fuzzy logic.

Table 5.18 shows the linguistic variables, their values, and associated fuzzy intervals.In the proposed model, membership function of distance (input 1) is represented in trapezoidal membership function and for better performance it has six membership variables viz. ( low, medium, medium high, high, very high , extreme). Similar to first input, the second input (SWL) had five triangular membership variables viz.(low, medium, medium high, high, very high), and the remaining inputs have three triangular membership functions as ( low, medium, high . The graphical representation of membership functions of the inputs as similar to Figure 5.2 shown in section 5.2.1.1. For Mamdani fuzzy system,the output variables had seven membership variables viz. (very low, low, medium, high, very high, extreme). This is also presented in Table 5.18.

Modeling of fuzzy logic system for frequency based noise prediction was implemented similar to the earlier implementation as discussed in section 5.2.1 . The details of implementation using different forms of fuzzy systems is presented in table 5.19. In this study, Centroid of area (COA) method of defuzzification is used. After defuzzication , the fuzzy models were tuned to minimize the error. The coefficients were set by trial and error basis and when the predictive value matched with the desired value with in the error limits, the coefficients were fixed. This treatment is quite different from other mathematical models or statistical model.

#### 5.3.1.2 Simulation results and discussion

The proposed models for noise prediction was validated using simulation studies. The studies were carried out by using MATLAB simulation environment. For validation of

Table 5.18: Inputs and output variables and their fuzzy intervals

| Sl.No. | System's linguistic variable | Variables | Linguistic values | Fuzzy interval |
|---|---|---|---|---|
| 1 | Inputs | SWL | Low | 80-100 dBA |
| | | | Medium | 90-110 dBA |
| | | | Medium High | 100-120 dBA |
| | | | High | 110-130 dBA |
| | | | Very High | 120-140 dBA |
| 2 | | Distance | Low | 5-40 meter |
| | | | Medium | 35-70 meter |
| | | | Medium High | 65-100 meter |
| | | | High | 95-130 meter |
| | | | Very High | 125-150 meter |
| | | | Extreme | 145-160 meter |
| 3 | | Wind | Low | 1-5 meter/sec |
| | | | Medium | 4-7 meter/sec |
| | | | High | 6-10 meter/sec |
| 4 | | Temperature | Low | 10-35 $^0$C |
| | | | Medium | 30-45 $^0$C |
| | | | High | 40-60 $^0$C |
| 5 | | Relative Humidity | Low | 10-45 % |
| | | | Medium | 40-60 % |
| | | | High | 55-100 % |
| 1 | Output | SPL | Very Low | 55-75 dBA |
| | | | Low | 70-85 dBA |
| | | | Medium | 80-90 dBA |
| | | | Medium High | 85-95 dBA |
| | | | High | 90-100 dBA |
| | | | Very High | 95-105 dBA |
| | | | Extreme | 100-115 dBA |

the models, the noise data was collected from Panchpatmali Bauxite Mine, National Aluminium Company Limited (NALCO), Damanjodi (Koraput, Odisha, India).The test data was measured using Brüel & Kjaer 2236 (Denmark) sound level meter. From the measured parameter, ISO-9613-2 gives prediction by calculating all the sound attenuations. SPL of the different machineries from the above mine was collected.

Fuzzy systems were applied for five frequency based noise prediction models. The classical noise prediction models are ISO-9613-2, CONCAWE, ENM, NORDFORSK and VDI-2720 standard was used as reference. Machinery noise prediction results were calculated as per the standards as discussed in Chapter 3 (Section 3.4.1 - 3.4.3). Fuzzy Inference Systems were applied to all frequency based noise prediction models. Performance of fuzzy system based noise prediction models for ISO-9613-2 model is discussed first. A set of 224 data points were first generated as per the ISO-9613-2 noise prediction model using (3.9). For this, the input parameters were distance, sound power level (SWL), wind speed, relative humidity and temperature. Using these input parameters, SPL was calculated. The root mean square error (RMSE) was used as the performance index, which was calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} ((ISO - 9613 - 2)_i - Estimated_i)^2}{N}} \tag{5.5}$$

Table 5.19: Application of Mamdani and T-S-K fuzzy models for frequency based noise prediction models

| Input parameters | Output Parameter | Frequency Dependent Models | Mamdani FIS | | | | TSK FIS | | | | Output of FISs |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Membership Function | Inference Engine | | Rule Base | Membership Function | Inference Engine | Functional Link | Rule Base | Defuzzification (Centriod Method) |
| | | | | Min | Max | | | Product | | | |
| 1. Distance<br>2. Sound Power Level<br>3. Wind<br>4. Relative Humidity<br>5. Temperature | Sound Pressure Level | CONCAWE<br>ENM<br>ISO-9613-2<br>VDI-2720<br>NORDFORSK | **Inputs**<br>Distance: Six<br>SWL: Five<br>Wind: Three<br>Temperature: Three<br>Relative Humidity: Three<br>**Output**<br>Sound Pressure Level: Seven | $W_1$=min $({}^1\mu_{dis}, {}^1\mu_{SWL}, {}^1\mu_{wind}, {}^1\mu_{temp}, {}^1\mu_{rh})$<br>$\mu_{min1}$=min($w_1$, ${}^1\mu_{SPL,Low}$)=[0.1, 0.2,.....0.9]<br>$W_{810}$=min $({}^6\mu_{dis}, {}^5\mu^3_{SWL}, \mu_{wind}, {}^3\mu^3_{temp}, \mu_{rh})$<br>$\mu_{min810}$=min($w_1$, ${}^7\mu_{SPL,Low}$)=[0.1, 0.2,.....0.9] | $\mu_{MAX}$= max[$\mu_{min1}$<br>.<br>.<br>.<br>.<br>.<br>.<br>$\mu_{min810}$] | Total Number of Rule = $(6\times5\times3\times3\times3)=810$ | **IInputs**<br>Distance: Six<br>SWL: Five<br>Wind: Three<br>Temperature: Three<br>Relative Humidity: Three<br>**Output**<br>Sound Pressure Level: Seven | $W_1={}^1\mu_{dis} \times {}^1\mu_{SWL} \times {}^1\mu_{wind} \times {}^1\mu_{temp} \times {}^1\mu_{rh}$<br>.<br>.<br>.<br>.<br>.<br>.<br>.<br>.<br>$W_{810}={}^6\mu_{dis} \times {}^5\mu_{SWL} \times {}^3\mu_{wind} \times {}^3\mu_{temp} \times {}^3\mu_{rh}$ | $F_1$= $a_1$A+$b_1$B $c_1$C+$d_1$D+ $e_1$E + +$K_1$<br>.<br>.<br>.<br>.<br>$F_{810}$= $a_{810}$A+$b_{810}$B+ $c_{810}$C+$d_{810}$D+ $e_{810}$E+$K_{810}$ | Total Number of Rule = $(6\times5\times3\times3\times3)=810$ | Mamdani FIS: $\sum \frac{\mu_{MAX} \times SPL}{\mu_{MAX}} = \sum_{i=1}^{810} \frac{\mu_z \times z}{\mu_z}$<br>T-S-K FIS: $\frac{F_1 \times w_1 + \ldots F_{810} \times w_{810}}{w_1 + \ldots + w_{810}} = \sum_{i=1}^{810} \frac{F_i \times w_i}{w_i}$ |

[a] $({}^1\mu_{dis}, {}^1\mu^1_{SWL}\mu_{wind}, {}^1\mu_{temp}, {}^1\mu_{rh}$ are the membership function of inputs)
[b] $a_1,b_1,c_1,d_1,e_1,K_1,.....a_{810},b_{810},c_{810},d_{810},e_{810},K_{810}$ are the coefficients of T-S-K fuzzy model.

Table 5.20 summarizes the results for noise prediction by proposed models and compares it with ISO-9613-2 noise prediction model for all selected opencast machineries. From the table it can be seen that the proposed Mamdani and T-S-K models provided RMSE of 3.4836 and 3.4671 respectively for Dozer. For Shovel, Dumper, Pay-loader, Rock-breaker, Rotary percussive drill and Roll crusher, the RMSE were 3.6473, 3.5829, 4.8581, 4.1440, 5.1335, 4.0297, 4.3098, 3.5386, 5.3392, 5.2970, 4.2653 and 4.6467 respectively. Similar study for other frequency based noise prediction models were investigated in this study. Comparison results of other frequency based noise prediction models with Mamdani and T-S-K were represented in Table 5.21 to 5.24. Table 5.21 represented the comparison result of CONCAWE noise prediction model, Table 5.22 represented the result of ENM model, Table 5.23 represented the result of NORDFORSK model and the Table 5.24 represented the comparison result of VDI-2720 model with Mamdani and T-S-K fuzzy inference system based noise prediction model. From the simulation studies, it was observed that the RMSE of Sugeno fuzzy model was lower than the Mamdani fuzzy model.

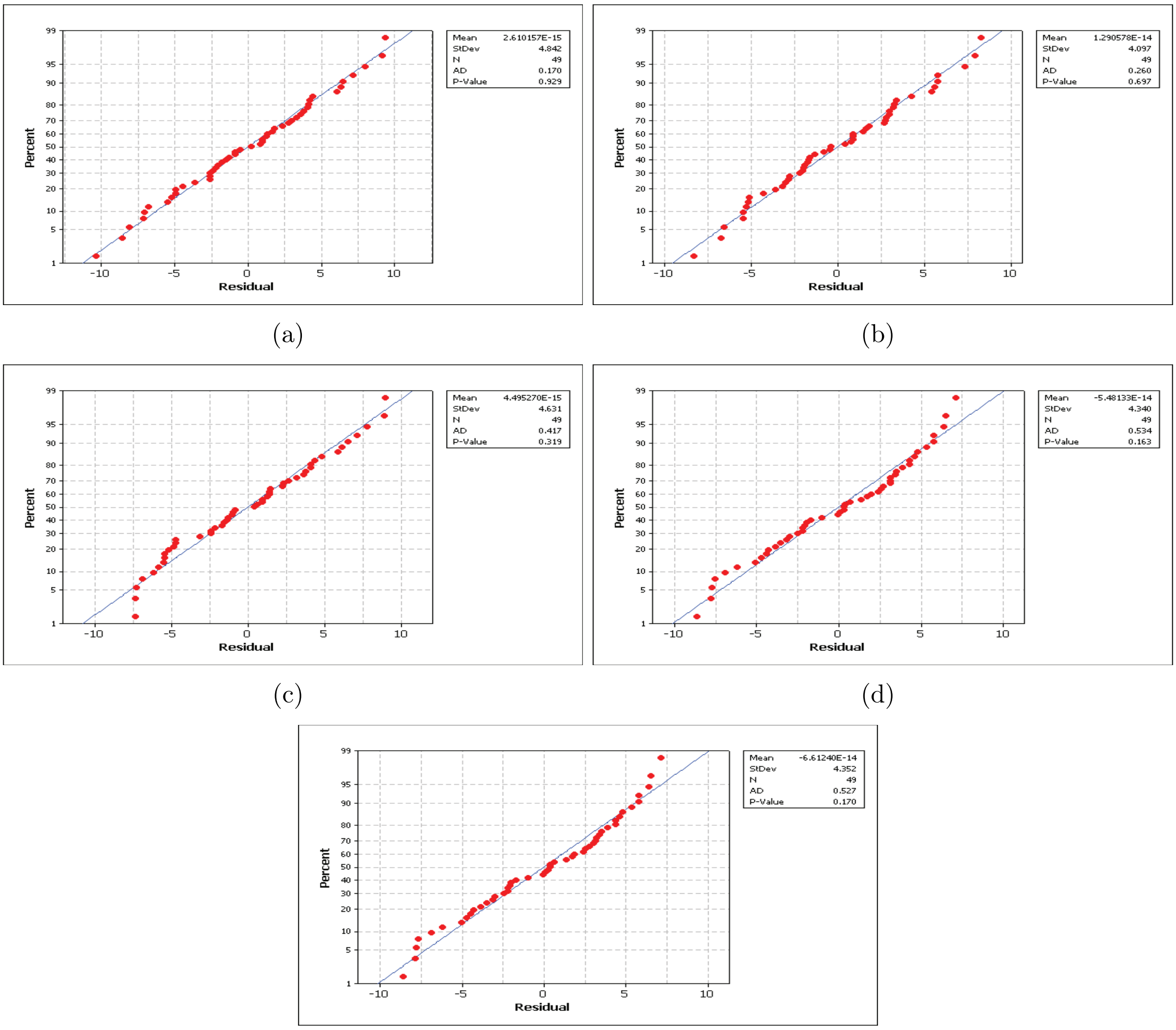
Anderson-Darling (AD) normality test results are shown in Figure 5.17 and Figure 5.18 for respective SPL residue. The test is done between the prediction results of Fuzzy systems (Mamdani and T-S-K) and frequency dependent model results. Figure 5.17 represented AD normality test for Mamdani fuzzy system, where Figure 5.18 represented the AD normality test for T-S-K fuzzy system. Since p-value of the normality plots are found to be above 0.05, it signifies that residue follows normal distribution. Small percentage of error proves the suitability of above models for practical engineering applications.

### 5.3.2 Application of Artificial Neural Network for Frequency based Noise Prediction

ANN models were used for implementing frequency based noise prediction for opencast mining machineries. Neural Network (MLP and RBFN) based prediction was implemented for ISO-9613-2, CONCAWE, ENM, NORDFORSK and VDI-2720 models. The selection of input and output for ANN model is same as fuzzy model as discussed in section 5.3.1 . The stepwise procedure, algorithm are similar to execution of ANN models for VDI-2714 discussed in section 5.2.2 . Table 5.25 represents the ANN procedure for all the frequency dependent models.

#### 5.3.2.1 Simulation Result and Discussion

ANN based frequency dependent noise prediction model was evaluated using,the same inputs as tested for Fuzzy system. In this study, ANN model was applied for five frequency based noise prediction models which include ISO-9613-2, VDI-2720, CONCAWE, NORDFORSK and ENM. Machinery noise was first calculated as per the prescribed



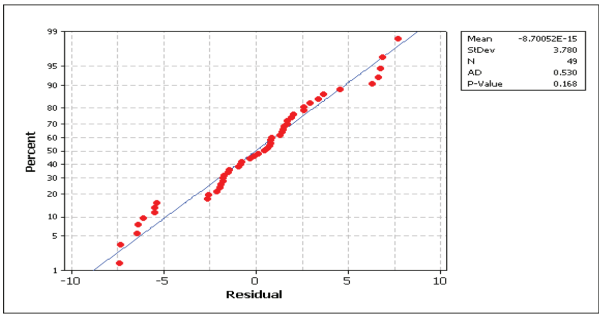

(a) (b)

(c) (d)

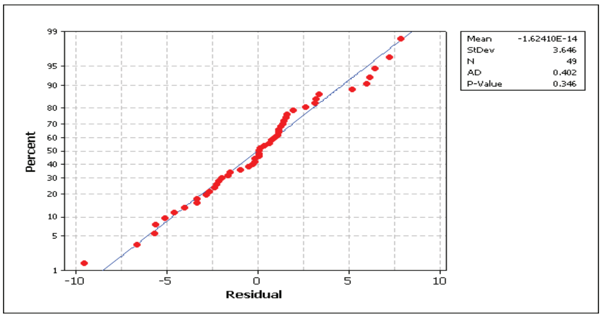
(e)

Figure 5.17: Statistical performance study of Mamdani Fuzzy Inference System based noise prediction(a)CONCAWE, (b)ISO-9613-2, (c) ENM, (d) NORDFORSK (e) VDI-2720

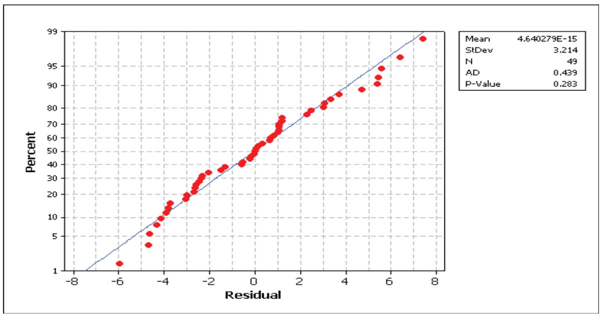
standards (Section 3.4.1 - 3.4.3, Chapter 3). Performance of ANN system based noise prediction models for ISO-9613-2 model is discussed first. For ANN system, 175 data samples were used as training data and 49 number of data samples were used as testing samples.Both MLP and RBF were used for developing noise prediction models. The ANN based noise prediction model result was compared with ISO-9613-2. In MLP based model, back propagation method was used to minimize the system error. MLP based noise prediction model gave good and appropriate result with five hidden nodes in hidden layer and this procedure was similar to MLP based model for VDI-2714 as discussed in previous section (5.2.2). The mean square error (MSE)of MLP model for 100 epochs is represented in Figure 5.19(a) and the performance of the MLP model for 49 testing



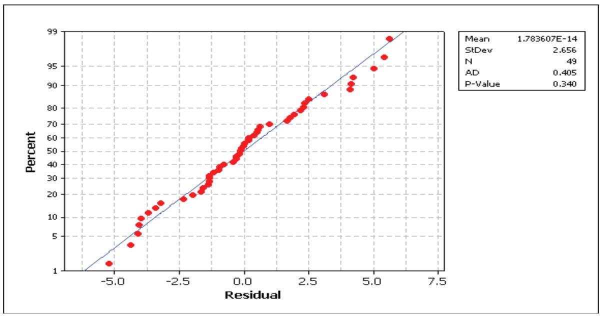

(a)



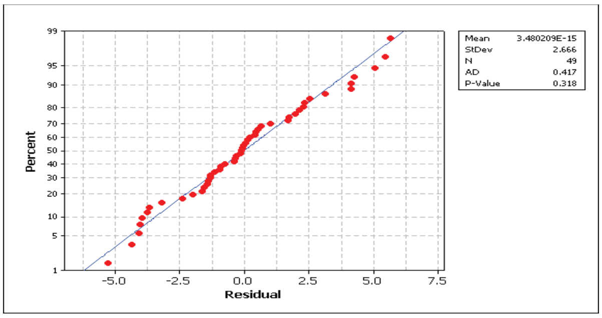

(b)




(c)



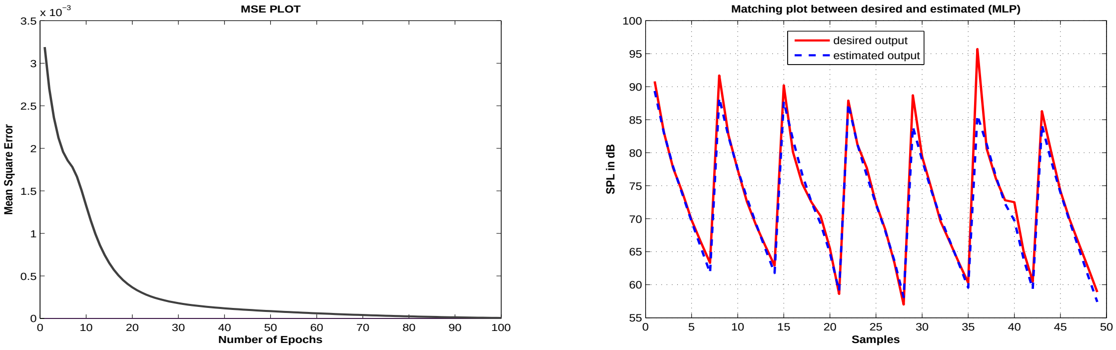

(d)




(e)

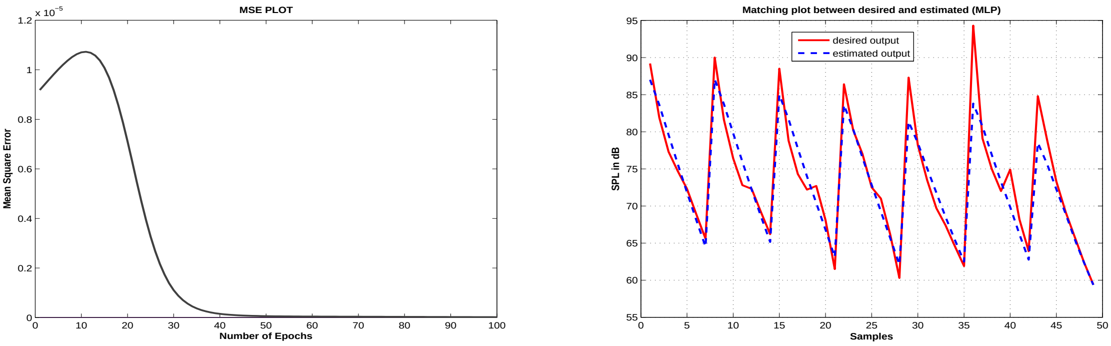
Figure 5.18: Statistical performance study of T-S-K Fuzzy Inference System based noise prediction(a)CONCAWE, (b)ISO-9613-2, (c) ENM, (d) NORDFORSK (e) VDI-2720

samples or validation samples is presented in Figure 5.19(b) . MSE plot of MLP for 100 epochs for CONCAWE model is represented in Fig 5.20 (a) and Fig. 5.20 (b) represented performance of MLP model for CONCAWE model prediction. Similarly Fig. 5.21(a) and 5.21(b) represented for ENM, Fig 5.22(a) and 5.22(b) represented for NORDFORSK and Fig 5.23(a) and 5.23(b) represented VDI-2720 model respectively.



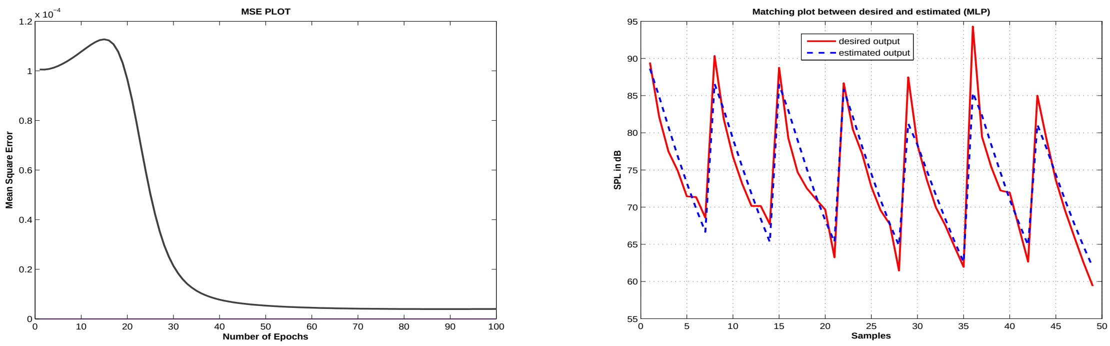

(a) (b)

Figure 5.19: (a) Mean square error plot of MLP system for 100 epochs (b) Prediction performance of MLP network for 49 samples for ISO-9613-2 noise prediction model




(a) (b)

Figure 5.20: (a) Mean square error plot of MLP system for 100 epochs (b) Prediction performance of MLP network for 49 samples for CONCAWE noise prediction model




(a) (b)

Figure 5.21: (a) Mean square error plot of MLP system for 100 epochs (b) Prediction performance of MLP network for 49 samples for ENM noise prediction model

Table 5.20: Comparative study between ISO-9613-2 and Fuzzy System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted ISO-9613-2 in dB(A) | Mamdani Predicted SPL in dB(A) | T-S-K Predicted SPL in dB(A) | Root mean square error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Mamdani | TSK |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 90 | 85.4 | 3.4836 | 3.4671 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 90 | 89.4 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 77.7 | 77.5 | 77.1 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 74.0 | 77.5 | 74.4 | | |
| | | 100 | 123.0 | 72.0 | 69.8 | 65.1 | 66.4 | | |
| | | 125 | 122.1 | 69.1 | 66.5 | 65.1 | 66.2 | | |
| | | 150 | 120.8 | 66.3 | 63.3 | 63.9 | 61.8 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 90 | 85.5 | 3.6473 | 3.5829 |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 90 | 87.2 | | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 77.4 | 77.5 | 77.1 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 72.6 | 77.5 | 74.1 | | |
| | | 100 | 122.0 | 71.0 | 69.0 | 65.6 | 63.7 | | |
| | | 125 | 121.4 | 68.4 | 65.9 | 64.9 | 66.4 | | |
| | | 150 | 120.4 | 65.9 | 62.9 | 63.5 | 62.2 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 90.1 | 83.8 | 4.8581 | 4.1440 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 90 | 85.3 | | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 75.3 | 77.5 | 76.9 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 72.5 | 77.4 | 74.2 | | |
| | | 100 | 122.9 | 71.9 | 70.4 | 67.3 | 65.8 | | |
| | | 125 | 120.7 | 67.7 | 65.5 | 64.7 | 67.1 | | |
| | | 150 | 115.9 | 61.4 | 58.6 | 63.9 | 63.4 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 90.1 | 85.2 | 5.1335 | 4.0297 |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 90.1 | 85.2 | | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 77.7 | 77.4 | 77.9 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 72.3 | 77.5 | 74.6 | | |
| | | 100 | 121.0 | 70.0 | 68.4 | 65.2 | 64.8 | | |
| | | 125 | 118.6 | 65.6 | 63.3 | 67.4 | 67.8 | | |
| | | 150 | 114.3 | 59.8 | 57.0 | 63.8 | 64.2 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 88.7 | 84.5 | 85 | 4.3098 | 3.5386 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 84.4 | 85.8 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 74.6 | 77.3 | 74.9 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 69.6 | 77.4 | 69.2 | | |
| | | 100 | 119.4 | 68.4 | 66.5 | 63.5 | 66.4 | | |
| | | 125 | 118.8 | 65.8 | 63.3 | 63.4 | 69.0 | | |
| | | 150 | 117.7 | 63.2 | 60.3 | 63.5 | 60.8 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 90.1 | 85.9 | 5.3392 | 5.2970 |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 90.1 | 80.3 | | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 76.1 | 77.4 | 77.4 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 77.4 | 74.5 | | |
| | | 100 | 123.8 | 72.8 | 72.5 | 66.1 | 63.6 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 66.9 | 67.6 | | |
| | | 150 | 116.1 | 61.6 | 60.5 | 63.8 | 63.7 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 84.9 | 81.7 | 4.2653 | 4.6467 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 84.9 | 80.3 | | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 74.2 | 77.5 | 77.6 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 77.5 | 73.7 | | |
| | | 100 | 117.5 | 66.5 | 66.2 | 64.1 | 69.5 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 64.1 | 71.7 | | |
| | | 150 | 114.7 | 60.2 | 58.9 | 64.1 | 62.1 | | |

Table 5.21: Comparative study between CONCAWE and Fuzzy System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted CONCAWE in dB(A) | Mamdani Predicted SPL in dB(A) | T-S-K Predicted SPL in dB(A) | Root mean square error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Mamdani | TSK |
| 1 | **DOZER** | 5 | 114.6 | 89.3 | 89.2 | 90 | 85.9458 | | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.2 | 82.2 | 81.9 | 90 | 84.0496 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 77.3 | 77.5 | 77.1314 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 74.7 | 77.5 | 74.3980 | 4.5245 | 2.9640 |
| | | 100 | 123 | 72.0 | 72.3 | 65.1 | 66.6877 | | |
| | | 125 | 122.1 | 69.1 | 68.9 | 65.1 | 68.3056 | | |
| | | 150 | 120.5 | 66.2 | 65.6 | 63.9 | 61.8165 | | |
| 2 | **SHOVEL** | 5 | 113.4 | 90.2 | 90 | 90 | 86.0127 | | |
| | (Wind Speed: 3.2 m/sec). | 25 | 120.9 | 81.9 | 81.6 | 90 | 82.0 | | |
| | (Temp. : $27^0$C) | 50 | 121.9 | 77.0 | 76.4 | 77.5 | 77.1314 | | |
| | (Relative humidity: 59 %) | 75 | 122.2 | 73.7 | 72.8 | 77.5 | 74.1080 | 4.8481 | 3.3688 |
| | | 100 | 121.9 | 70.9 | 72.3 | 65.6 | 65.7353 | | |
| | | 125 | 121.4 | 68.4 | 69.2 | 64.9 | 67.7346 | | |
| | | 150 | 120.4 | 65.9 | 66.2 | 63.5 | 62.2130 | | |
| 3 | **DUMPER** | 5 | 113.6 | 88.6 | 88.5 | 90.1 | 86.3118 | | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.2 | 79.1 | 78.8 | 90 | 86.4441 | | |
| | (Temp. : $29^0$C) | 50 | 119.8 | 74.9 | 74.3 | 77.5 | 76.8592 | | |
| | (Relative humidity: 58 %) | 75 | 121.5 | 73 | 72.2 | 77.4 | 74.2500 | 5.5001 | 3.9837 |
| | | 100 | 122.8 | 71.8 | 72.7 | 67.3 | 66.9626 | | |
| | | 125 | 120.6 | 67.6 | 68.1 | 64.7 | 67.6264 | | |
| | | 150 | 115.8 | 61.3 | 61.5 | 63.9 | 63.4934 | | |
| 4 | **PAYLOADER** | 5 | 111.5 | 86.5 | 86.4 | 90.1 | 86.3128 | | |
| | (Wind Speed: 3 m/sec) | 25 | 119.5 | 80.5 | 80.2 | 90.1 | 86.5972 | | |
| | (Temp. : $30^0$C) | 50 | 122.3 | 77.4 | 77.0 | 77.4 | 77.9114 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 72.5 | 77.5 | 74.6280 | 5.1296 | 3.6107 |
| | | 100 | 121.0 | 70.0 | 71.0 | 65.2 | 65.8240 | | |
| | | 125 | 118.6 | 65.6 | 66.2 | 67.4 | 67.8261 | | |
| | | 150 | 114.2 | 59.7 | 60.3 | 63.8 | 64.2414 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.4 | 87.4 | 87.3 | 84.5 | 87.6906 | | |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.5 | 78.5 | 78.2 | 84.4 | 85.1172 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 73.5 | 77.3 | 74.9012 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 69.7 | 77.4 | 69.2778 | 4.4597 | 3.2217 |
| | | 100 | 117.3 | 66.3 | 67.4 | 63.5 | 66.6576 | | |
| | | 125 | 116.6 | 63.6 | 64.6 | 63.4 | 69.2491 | | |
| | | 150 | 115.6 | 61.1 | 61.9 | 63.5 | 62.4914 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 94.3 | 90.1 | 86.8671 | | |
| | (Wind Speed: 2 m/sec) | 25 | 118.4 | 79.4 | 79.1 | 90.1 | 85.3398 | | |
| | (Temp. : $30^0$C) | 50 | 120.5 | 75.6 | 75.0 | 77.4 | 77.3714 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.0 | 77.4 | 74.4980 | 6.0083 | 4.7017 |
| | | 100 | 123.7 | 72.7 | 74.9 | 66.1 | 67.9427 | | |
| | | 125 | 118.7 | 65.7 | 68.2 | 66.9 | 67.6717 | | |
| | | 150 | 116.0 | 61.5 | 63.9 | 63.8 | 63.8014 | | |
| 7 | **ROLL CRUSHER** | 5 | 109.9 | 84.9 | 84.8 | 84.9 | 83.1829 | | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 78.9 | 84.9 | 81.4471 | | |
| | (Temp. : $32^0$C) | 50 | 118.6 | 73.7 | 73.3 | 77.5 | 77.6060 | | |
| | (Relative humidity: 58 %) | 75 | 118.3 | 69.8 | 69.2 | 77.5 | 73.6933 | 4.6354 | 5.0831 |
| | | 100 | 114.2 | 63.2 | 65.8 | 64.1 | 68.8856 | | |
| | | 125 | 112.9 | 59.9 | 62.4 | 64.1 | 71.1211 | | |
| | | 150 | 111.6 | 57.1 | 59.4 | 64.1 | 66.2888 | | |

Table 5.22: Comparative study between ENM and Fuzzy System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted ENM in dB(A) | Mamdani Predicted SPL in dB(A) | T-S-K Predicted SPL in dB(A) | Root mean square error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Mamdani | TSK |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 92.4 | 90 | 87.4918 | 6.0617 | 4.8810 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 85.0 | 90 | 83.3035 | | |
| | (Temp. : 28$^0$C) | 50 | 122.7 | 77.8 | 80.3 | 77.5 | 77.1314 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 77.7 | 77.5 | 74.3980 | | |
| | | 100 | 123.0 | 72.0 | 74.2 | 65.1 | 67.8642 | | |
| | | 125 | 122.1 | 69.1 | 74.1 | 65.1 | 69.4167 | | |
| | | 150 | 120.8 | 66.3 | 71.3 | 63.9 | 63.7647 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 93.3 | 90 | 88.6543 | 5.4883 | 4.3663 |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 84.7 | 90 | 82.0790 | | |
| | (Temp. : 27$^0$C) | 50 | 122.1 | 77.2 | 79.6 | 77.5 | 77.1914 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 75.9 | 77.5 | 74.1380 | | |
| | | 100 | 122.0 | 71.0 | 72.9 | 65.6 | 66.9277 | | |
| | | 125 | 121.4 | 68.4 | 72.9 | 64.9 | 68.2484 | | |
| | | 150 | 120.4 | 65.9 | 70.4 | 63.5 | 64.1722 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 91.7 | 90.1 | 86.7552 | 4.9989 | 3.6270 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 82.1 | 90 | 86.5752 | | |
| | (Temp. : 29$^0$C) | 50 | 120.0 | 75.1 | 77.5 | 77.5 | 76.9034 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 75.3 | 77.4 | 74.2800 | | |
| | | 100 | 122.9 | 71.9 | 73.8 | 67.3 | 68.2181 | | |
| | | 125 | 120.7 | 67.7 | 72.4 | 64.7 | 68.7295 | | |
| | | 150 | 115.9 | 61.4 | 65.9 | 63.9 | 64.6434 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 89.6 | 90.1 | 83.2782 | 4.0839 | 3.5934 |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 83.3 | 90.1 | 86.7782 | | |
| | (Temp. : 30$^0$C) | 50 | 122.4 | 77.5 | 80.0 | 77.4 | 77.9414 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 75.5 | 77.5 | 74.6280 | | |
| | | 100 | 121.0 | 70.0 | 72.3 | 65.2 | 66.8766 | | |
| | | 125 | 118.6 | 65.6 | 70.4 | 67.4 | 68.6761 | | |
| | | 150 | 114.3 | 59.8 | 64.1 | 63.8 | 65.0714 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 90.4 | 84.5 | 85.6139 | 4.3298 | 3.5420 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 81.2 | 84.4 | 86.6795 | | |
| | (Temp. : 29$^0$C) | 50 | 119.0 | 74.1 | 76.5 | 77.3 | 75.8112 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 72.7 | 77.4 | 71.0978 | | |
| | | 100 | 119.4 | 68.4 | 70.3 | 63.5 | 66.4476 | | |
| | | 125 | 118.8 | 65.8 | 67.4 | 63.4 | 69.0291 | | |
| | | 150 | 117.7 | 63.2 | 64.6 | 63.5 | 60.8114 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 97.3 | 90.1 | 95.8939 | 5.4103 | 2.5743 |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 82.3 | 90.1 | 85.7453 | | |
| | (Temp. : 30$^0$C) | 50 | 120.8 | 75.9 | 78.2 | 77.4 | 77.4614 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 75.0 | 77.4 | 74.4980 | | |
| | | 100 | 123.8 | 72.8 | 74.7 | 66.1 | 69.2691 | | |
| | | 125 | 118.7 | 65.7 | 70.0 | 66.9 | 68.5317 | | |
| | | 150 | 116.1 | 61.6 | 65.3 | 63.8 | 64.9914 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 87.9 | 84.9 | 90.4948 | 3.2300 | 2.2435 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 81.9 | 84.9 | 83.3035 | | |
| | (Temp. : 32$^0$C) | 50 | 118.7 | 73.8 | 76.4 | 77.5 | 77.1314 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 72.3 | 77.5 | 74.3980 | | |
| | | 100 | 117.5 | 66.5 | 68.7 | 64.1 | 67.8642 | | |
| | | 125 | 116.2 | 63.2 | 65.2 | 64.1 | 69.4167 | | |
| | | 150 | 114.7 | 60.2 | 62.0 | 64.1 | 63.7647 | | |

Table 5.23: Comparative study between NORDFORSK and Fuzzy System based models

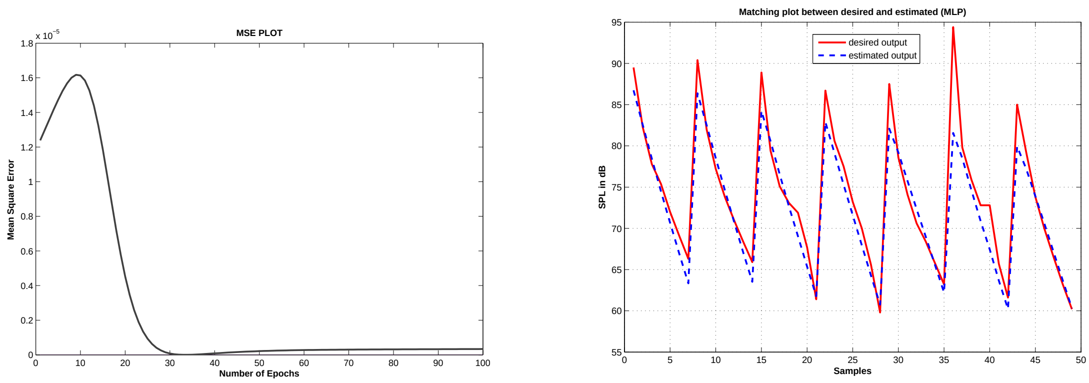
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted NORDFORSK WE in dB(A) | Mamdani Predicted SPL in dB(A) | T-S-K Predicted SPL in dB(A) | Root mean square error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Mamdani | TSK |
| 1 | **DOZER** (Wind Speed: 2.5 m/sec) (Temp. : $28^0$C) (Relative humidity: 57 %) | 5 | 114.5 | 89.5 | 90.8 | 84.9999 | 89.7118 | 4.1206 | 1.5150 |
| | | 25 | 121.3 | 82.3 | 83.1 | 84.9999 | 82.1869 | | |
| | | 50 | 122.7 | 77.8 | 78.0 | 77.4998 | 77.1314 | | |
| | | 75 | 123.9 | 75.4 | 75.1 | 77.4998 | 74.3980 | | |
| | | 100 | 123.0 | 72.0 | 71.4 | 64.0183 | 69.5465 | | |
| | | 125 | 122.1 | 69.1 | 68.4 | 64.0183 | 70.9944 | | |
| | | 150 | 120.8 | 66.3 | 65.4 | 64.0183 | 67.0231 | | |
| 2 | **SHOVEL** (Wind Speed: 3.2 m/sec) (Temp. : $27^0$C) (Relative humidity: 59 %) | 5 | 115.4 | 90.4 | 91.7 | 84.9999 | 91.0223 | 4.1556 | 1.8345 |
| | | 25 | 121.0 | 82.0 | 82.7 | 84.9999 | 81.7000 | | |
| | | 50 | 122.1 | 77.2 | 77.3 | 77.4998 | 77.1914 | | |
| | | 75 | 122.3 | 73.8 | 73.6 | 77.4998 | 74.1380 | | |
| | | 100 | 122.0 | 71.0 | 70.5 | 64.0183 | 68.8610 | | |
| | | 125 | 121.4 | 68.4 | 67.6 | 64.0183 | 70.6875 | | |
| | | 150 | 120.4 | 65.9 | 64.8 | 64.0183 | 67.8947 | | |
| 3 | **DUMPER** (Wind Speed: 2.91 m/sec) (Temp. : $29^0$C) (Relative humidity: 58 %) | 5 | 113.9 | 88.9 | 90.2 | 84.9999 | 89.1212 | 4.6220 | 3.6512 |
| | | 25 | 118.4 | 79.4 | 80.1 | 84.9999 | 85.9032 | | |
| | | 50 | 120.0 | 75.1 | 75.3 | 77.4998 | 76.9034 | | |
| | | 75 | 121.6 | 73.1 | 73.1 | 77.4998 | 74.2800 | | |
| | | 100 | 122.9 | 71.9 | 71.2 | 64.0183 | 70.0555 | | |
| | | 125 | 120.7 | 67.7 | 67.0 | 64.0183 | 70.3728 | | |
| | | 150 | 115.9 | 61.4 | 60.3 | 64.0183 | 66.7674 | | |
| 4 | **PAYLOADER** (Wind Speed: 3 m/sec) (Temp. : $30^0$C) (Relative humidity: 58 %) | 5 | 111.7 | 86.7 | 87.9 | 84.9999 | 85.7762 | 3.8080 | 4.0316 |
| | | 25 | 119.6 | 80.6 | 81.2 | 84.9999 | 86.0102 | | |
| | | 50 | 122.4 | 77.5 | 77.7 | 77.4998 | 77.9414 | | |
| | | 75 | 121.7 | 73.2 | 73.1 | 77.4998 | 74.6280 | | |
| | | 100 | 121.0 | 70.0 | 69.7 | 64.0183 | 68.5503 | | |
| | | 125 | 118.6 | 65.6 | 64.9 | 64.0183 | 70.0361 | | |
| | | 150 | 114.3 | 59.8 | 58.9 | 64.0183 | 66.3854 | | |
| 5 | **ROCK-BREAKER** (Wind Speed: 7.1 m/sec) (Temp. : $29^0$C) (Relative humidity: 61 %) | 5 | 112.5 | 87.5 | 88.7 | 84.9999 | 86.6139 | 4.1745 | 3.2414 |
| | | 25 | 117.6 | 78.6 | 79.4 | 84.9999 | 85.9195 | | |
| | | 50 | 119.0 | 74.1 | 74.5 | 77.4998 | 76.7212 | | |
| | | 75 | 119.1 | 70.6 | 70.6 | 77.4998 | 72.0078 | | |
| | | 100 | 119.4 | 68.4 | 68.0 | 64.0183 | 66.4476 | | |
| | | 125 | 118.8 | 65.8 | 65.1 | 64.0183 | 69.0291 | | |
| | | 150 | 117.7 | 63.2 | 62.2 | 64.0183 | 60.8114 | | |
| 6 | **ROTARY PERCUSSIVE DRILL** (Wind Speed: 2 m/sec) (Temp. : $30^0$C) (Relative humidity: 59 %) | 5 | 119.4 | 94.4 | 95.7 | 84.9999 | 97.9539 | 5.8568 | 3.7554 |
| | | 25 | 118.8 | 79.8 | 80.6 | 84.9999 | 85.3933 | | |
| | | 50 | 120.8 | 75.9 | 76.1 | 77.4998 | 77.4614 | | |
| | | 75 | 121.3 | 72.8 | 72.8 | 77.4998 | 74.4980 | | |
| | | 100 | 123.8 | 72.8 | 72.5 | 64.0183 | 71.3506 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 64.0183 | 70.0797 | | |
| | | 150 | 116.1 | 61.6 | 61.0 | 64.0183 | 67.3094 | | |
| 7 | **ROLL CRUSHER** (Wind Speed: 7 m/sec) (Temp. : $32^0$C) (Relative humidity: 58 %) | 5 | 110.0 | 85.0 | 86.3 | 84.9999 | 82.0372 | 4.1938 | 5.3202 |
| | | 25 | 118.2 | 79.2 | 80.1 | 84.9999 | 81.8688 | | |
| | | 50 | 118.7 | 73.8 | 74.1 | 77.4998 | 78.0635 | | |
| | | 75 | 118.4 | 69.9 | 69.9 | 77.4998 | 74.3554 | | |
| | | 100 | 117.5 | 66.5 | 66.2 | 64.0183 | 69.5362 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 64.0183 | 71.7717 | | |
| | | 150 | 114.7 | 60.2 | 59.4 | 64.0183 | 66.1837 | | |

Table 5.24: Comparative study between VDI-2720 and Fuzzy System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted VDI-2720 in dB(A) | Mamdani Predicted SPL in dB(A) | T-S-K Predicted SPL in dB(A) | Root mean square error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Mamdani | TSK |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 84.9999 | 89.7118 | 4.1206 | 1.5150 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 84.9999 | 82.1869 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 78.0 | 77.4998 | 77.1314 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 75.2 | 77.4998 | 74.3980 | | |
| | | 100 | 123.0 | 72.0 | 71.4 | 64.0183 | 69.5465 | | |
| | | 125 | 122.1 | 69.1 | 68.4 | 64.0183 | 70.9944 | | |
| | | 150 | 120.8 | 66.3 | 65.4 | 64.0183 | 67.0231 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 84.9999 | 91.0223 | 4.1556 | 1.8345 |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 84.9999 | 81.7000 | | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 77.4 | 77.4998 | 77.1914 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 73.6 | 77.4998 | 74.1380 | | |
| | | 100 | 122.0 | 71.0 | 70.5 | 64.0183 | 68.8610 | | |
| | | 125 | 121.4 | 68.4 | 67.7 | 64.0183 | 70.6875 | | |
| | | 150 | 120.4 | 65.9 | 64.9 | 64.0183 | 67.8947 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 84.9999 | 89.1212 | 4.6220 | 3.6512 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 84.9999 | 85.9032 | | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 75.3 | 77.4998 | 76.9034 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 73.1 | 77.4998 | 74.2800 | | |
| | | 100 | 122.9 | 71.9 | 71.6 | 64.0183 | 70.0555 | | |
| | | 125 | 120.7 | 67.7 | 67.0 | 64.0183 | 70.3728 | | |
| | | 150 | 115.9 | 61.4 | 60.4 | 64.0183 | 66.7674 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 84.9999 | 85.7762 | 3.8080 | 4.0316 |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 84.9999 | 86.0102 | | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 77.7 | 77.4998 | 77.9414 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 73.1 | 77.4998 | 74.6280 | | |
| | | 100 | 121.0 | 70.0 | 69.7 | 64.0183 | 68.5503 | | |
| | | 125 | 118.6 | 65.6 | 65.0 | 64.0183 | 70.0361 | | |
| | | 150 | 114.3 | 59.8 | 58.9 | 64.0183 | 66.3854 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 88.7 | 84.9999 | 86.6139 | 4.1745 | 3.2414 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 84.9999 | 85.9195 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 74.6 | 77.4998 | 76.7212 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 70.6 | 77.4998 | 72.0078 | | |
| | | 100 | 119.4 | 68.4 | 68.0 | 64.0183 | 66.4476 | | |
| | | 125 | 118.8 | 65.8 | 65.1 | 64.0183 | 69.0291 | | |
| | | 150 | 117.7 | 63.2 | 62.3 | 64.0183 | 60.8114 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 84.9999 | 97.9539 | 5.8568 | 3.7554 |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 84.9999 | 85.3933 | | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 76.1 | 77.4998 | 77.4614 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 77.4998 | 74.4980 | | |
| | | 100 | 123.8 | 72.8 | 72.5 | 64.0183 | 71.3506 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 64.0183 | 70.0797 | | |
| | | 150 | 116.1 | 61.6 | 61.0 | 64.0183 | 67.3094 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 84.9999 | 82.0372 | 4.1938 | 5.3202 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 84.9999 | 81.8688 | | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 74.2 | 77.4998 | 78.0635 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 77.4998 | 74.3554 | | |
| | | 100 | 117.5 | 66.5 | 66.2 | 64.0183 | 69.5362 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 64.0183 | 71.7717 | | |
| | | 150 | 114.7 | 60.2 | 59.4 | 64.0183 | 66.1837 | | |

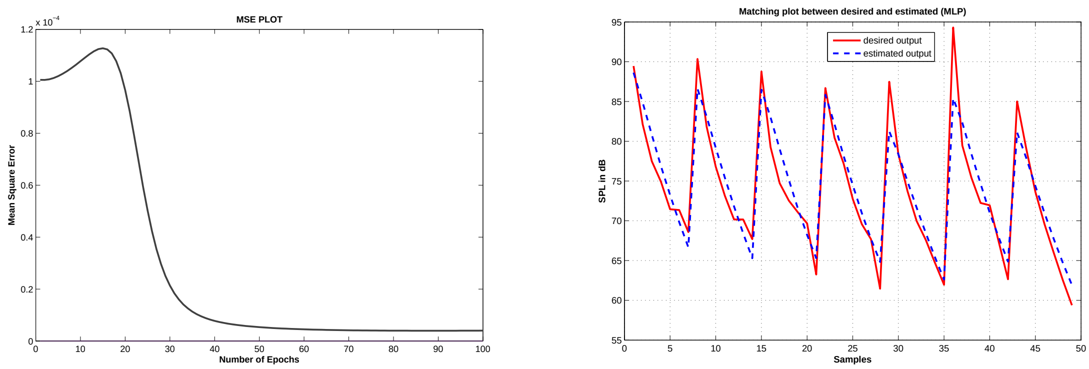
Table 5.25: Application of Artificial Neural Network (ANN) models for frequency based noise prediction models

| Input parameters | Output Parameter | Frequency Dependent Models | MLP (Multilayer Perceptron) | | RBF (Radial Basis Function) | | Error Updating for MLP and RBF |
|---|---|---|---|---|---|---|---|
| | | | Input-hidden-output nodes | Activation Function | No. of Centers | Function used for system design | |
| 1. Distance<br>2. Sound Power Level<br>3. Wind<br>4. Relative Humidity<br>5. Temperature | Sound Pressure Level (SPL) | CONCAWE<br>ENM<br>ISO-9613-2<br>VDI-2720<br>NORDFORSK | One input layer, one hidden and one output layer Five number of hidden units are selected in hidden layer for better performance (5-5-1) | Logsigmoid Activation function was used for hidden layer, where purelin (linear) activation function was used for output layer. | K-mean clustering method was used for selecting the centers. In this system 30 centers was given very good performance compare to others. | **Calculate the RBF Network Output** Gussain function was used to obtained output of RBFN network | Least Mean Sqaure Method was used for error updating. |




(a) (b)

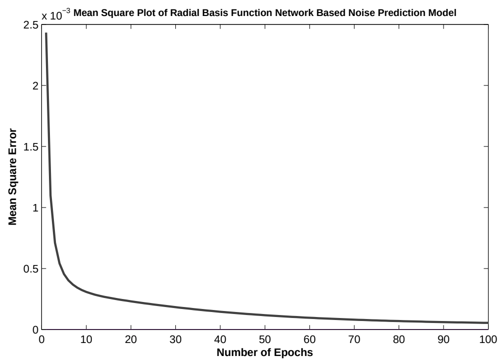
Figure 5.22: (a) Mean square error plot of MLP system for 100 epochs (b) Prediction performance of MLP network for 49 samples for NORDFORSK noise prediction model



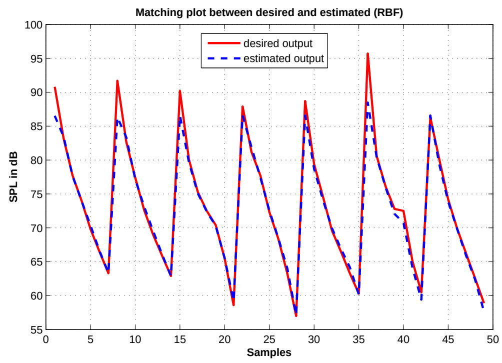

(a) (b)

Figure 5.23: (a) Mean square error plot of MLP system for 100 epochs (b) Prediction performance of MLP network for 49 samples for VDI-2720 noise prediction model

Similar to MLP prediction, RBFN based noise prediction model was also developed. This model has an input layer, hidden layer was varied from 5 to 100. In this system, thirty centers were selected for better performance of the model. Gaussian Function was used in hidden layer, for which the centers were determined by K-mean clustering. For proper comparison, the output of ISO-9613-2 model was scaled between 0 to 1. The all procedures was also similar to development RBF noise prediction model for VDI-2714 (section). Similar to MLP model, the mean square (MSE) of RBF model for 100 epochs was represented in Fig 5.24(a) and the performance of the RBF model for 49 testing samples is represented in Fig. 5.24(b) . For both MLP and RBF, RMSE was used as the performance index. MSE plot of RBF system for 100 epochs for CONCAWE model is represented in Fig 5.25(a), Fig. 5.25(b) represented performance of RBF model for CONCAWE. Similarly Fig. 5.26(a) and 5.26(b) represented for ENM, Fig 5.27(a) and 5.27(b) represented for NORDFORSK and Fig 5.28(a) and 5.28(b) represented the VDI-2720 model performance.



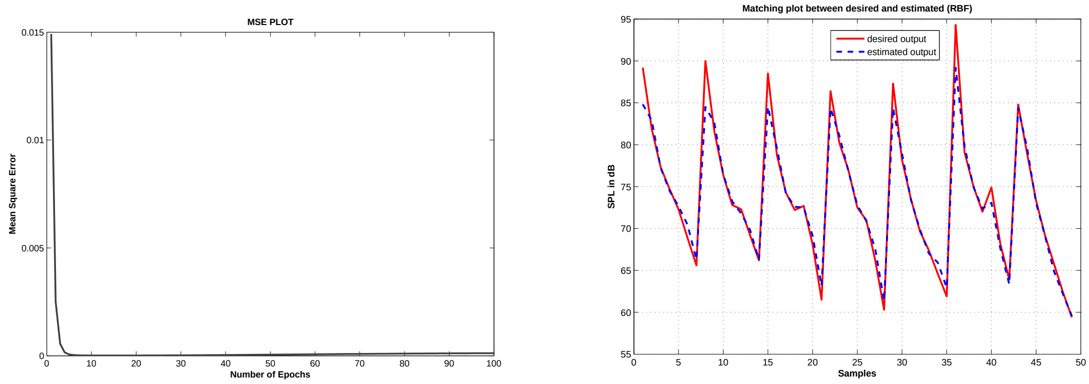

(a)




(b)

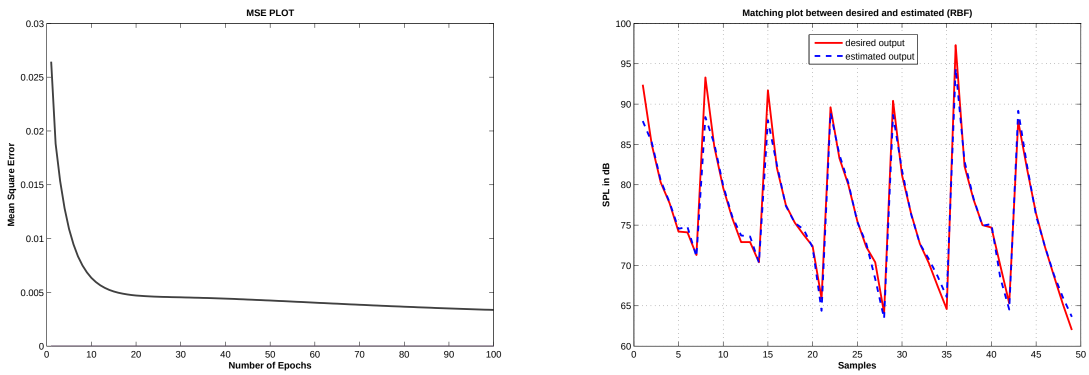
Figure 5.24: (a) Mean square error plot of RBF system for 100 epochs (b) Prediction performance of RBF network for 49 samples for ISO-9613-2 noise prediction model

Table 5.26 summarizes the results for noise prediction by the developed models and compares with ISO-9613-2 model for all selected machineries. From Table 5.26, it can be seen that MLP and RBF models provided root mean square error of 1.7865 and 2.09.8 for Dozer. For Shovel, the RMSE was 1.7716 and 2.9686, for Dumper, RMSE was 2.0213 and 1.4957, for Pay-Loader, RMSE was 1.2801 and 0.5490. For Rock-Breaker, RMSE of MLP and RBF systems was 2.2567 and 0.9196, for Rotary Drill, RMSE was found as 3.9812 and 3.2518 , for Roll-Crusher, RMSE was found to be 1.6690 and 0.7635. respectively. Comparative results of other frequency based noise prediction model with MLP and RBF were represented in Table 5.27 to 5.30. Table 5.27 represented the comparison result of CONCAWE noise prediction model, Table 5.28 represent the result of ENM model, Table 5.29 represent the result of NORDFORSK model where as Table 5.30 represented the



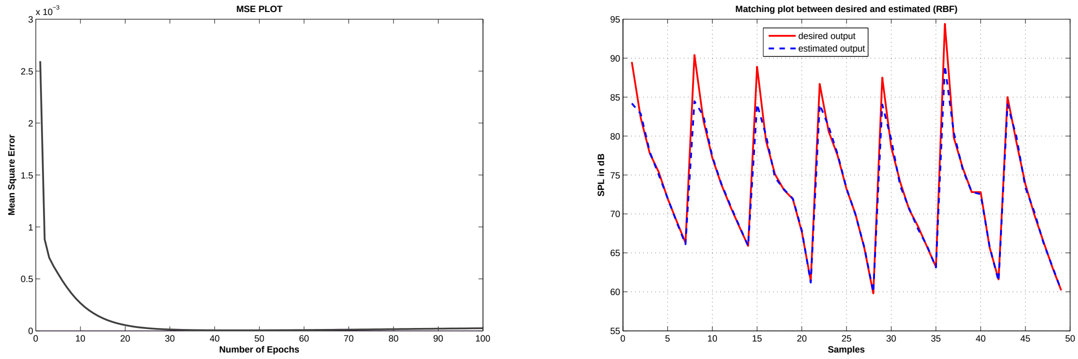

(a) (b)

Figure 5.25: (a) Mean square error plot of RBF system for 100 epochs (b) Prediction performance of RBF network for 49 samples for CONCAWE noise prediction model



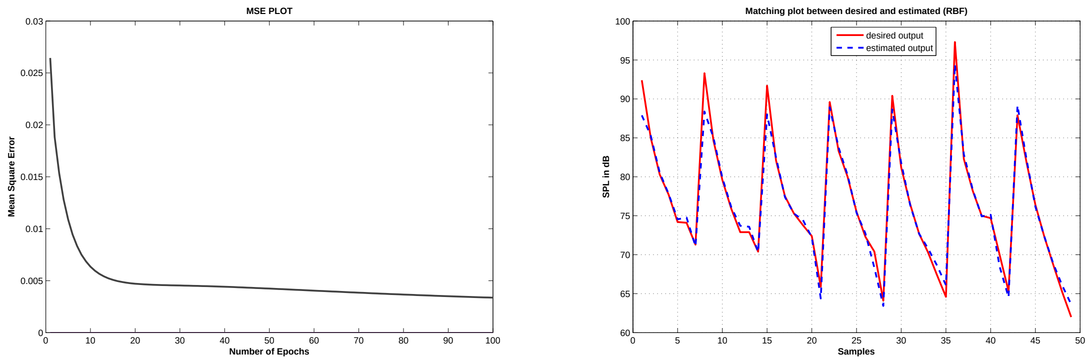

(a) (b)

Figure 5.26: (a) Mean square error plot of RBF system for 100 epochs (b) Prediction performance of RBF network for 49 samples for ENM noise prediction model




(a) (b)

Figure 5.27: (a) Mean square error plot of RBF system for 100 epochs (b) Prediction performance of RBF network for 49 samples for NORDFORSK noise prediction model




(a) (b)

Figure 5.28: (a) Mean square error plot of RBF system for 100 epochs (b) Prediction performance of RBF network for 49 samples for VDI-2720 noise prediction model

comparison result of VDI-2720 model with MLP and RBF system based noise prediction model.

Anderson-Darling (AD) normality test results are shown in Figure 5.29 and Figure 5.30 for respective SPL residue. The test is done between the prediction results of ANN systems (MLP and RBF) and frequency dependent model results. Figure 5.29 represent AD normality test for MLP system, where Figure 5.30 represent the AD normality test for RBF fuzzy system. Since p-value of the normality plots are found to be above 0.05, it signifies that residue follows normal distribution. Small percentage of error proves the suitability of above models for practical engineering applications.

Table 5.26: Comparative study between ISO-9613-2 and ANN System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted SPL ISO-9613-2 in dB(A) | MLP Predicted SPL in dB(A) | RBF Predicted SPL in dB(A) | RMSE error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MLP | RBF |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 87.1 | 85.4 | | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 84.1 | 83.6 | | |
| | (Temp. : 28C) | 50 | 122.7 | 77.8 | 77.7 | 78.7 | 77.3 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 74.0 | 73.8 | 73.3 | 1.7865 | 2.0908 |
| | | 100 | 123.0 | 72.0 | 69.8 | 69.2 | 70.5 | | |
| | | 125 | 122.1 | 69.1 | 66.5 | 65.0 | 66.7 | | |
| | | 150 | 120.8 | 66.3 | 63.3 | 61.3 | 63.2 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 87.4 | 83.9 | | |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 83.2 | 83.2 | | |
| | (Temp. : 27C) | 50 | 122.1 | 77.2 | 77.4 | 78.0 | 76.9 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 72.6 | 73.2 | 72.9 | 1.7716 | 2.9686 |
| | | 100 | 122.0 | 71.0 | 69.0 | 68.9 | 69.4 | | |
| | | 125 | 121.4 | 68.4 | 65.9 | 65.0 | 66.2 | | |
| | | 150 | 120.4 | 65.9 | 62.9 | 61.6 | 63.0 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 86.6 | 86.5 | | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 82.5 | 81.0 | | |
| | (Temp. : 29C) | 50 | 120.0 | 75.1 | 75.3 | 77.2 | 74.8 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 72.5 | 72.6 | 72.6 | 2.0213 | 1.4957 |
| | | 100 | 122.9 | 71.9 | 70.4 | 68.5 | 70.4 | | |
| | | 125 | 120.7 | 67.7 | 65.5 | 64.4 | 65.8 | | |
| | | 150 | 115.9 | 61.4 | 58.6 | 59.8 | 59.5 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 85.7 | 87.7 | | |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 81.9 | 81.6 | | |
| | (Temp. : 30C) | 50 | 122.4 | 77.5 | 77.7 | 76.8 | 77.1 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 72.3 | 72.1 | 72.6 | 1.2801 | 0.5490 |
| | | 100 | 121.0 | 70.0 | 68.4 | 67.8 | 68.3 | | |
| | | 125 | 118.6 | 65.6 | 63.3 | 63.6 | 64.2 | | |
| | | 150 | 114.3 | 59.8 | 57.0 | 59.2 | 57.8 | | |
| 5 | **ROCK-BREAKER**) | 5 | 112.5 | 87.5 | 88.7 | 82.8 | 87.6 | | |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 78.9 | 81.0 | | |
| | (Temp. : 29C) | 50 | 119.0 | 74.1 | 74.6 | 74.3 | 73.8 | | |
| | (Relative humidity: 61 % | 75 | 119.1 | 70.6 | 69.6 | 70.2 | 70.1 | 2.2567 | 0.9196 |
| | | 100 | 119.4 | 68.4 | 66.5 | 66.6 | 66.6 | | |
| | | 125 | 118.8 | 65.8 | 63.3 | 63.5 | 64.4 | | |
| | | 150 | 117.7 | 63.2 | 60.3 | 60.6 | 60.1 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 86.2 | 87.3 | | |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 81.8 | 81.1 | | |
| | (Temp. : 30C) | 50 | 120.8 | 75.9 | 76.1 | 76.7 | 75.7 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 72.1 | 72.4 | 3.9812 | 3.2518 |
| | | 100 | 123.8 | 72.8 | 72.5 | 68.4 | 71.3 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 63.9 | 64.3 | | |
| | | 150 | 116.1 | 61.6 | 60.5 | 60.1 | 59.6 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 82.3 | 87.8 | | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 78.7 | 81.0 | | |
| | (Temp. : 32C) | 50 | 118.7 | 73.8 | 74.2 | 73.9 | 73.6 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 69.5 | 69.7 | 1.6690 | 0.7635 |
| | | 100 | 117.5 | 66.5 | 66.2 | 65.5 | 66.3 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 61.8 | 62.0 | | |
| | | 150 | 114.7 | 60.2 | 58.9 | 58.5 | 58.4 | | |

Table 5.27: Comparative study between CONCAWE and ANN System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted CONCAWE in dB(A) | MLP Predicted SPL in dB(A) | RBF Predicted SPL in dB(A) | RMSE error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MLP | RBF |
| 1 | **DOZER** | 5 | 114.6 | 89.3 | 89.2 | 85.9255 | 84.8003 | 1.6240 | 1.8896 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.2 | 82.2 | 81.9 | 82.6077 | 83.1144 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 77.3 | 78.7162 | 77.1816 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 74.7 | 74.9369 | 74.7608 | | |
| | | 100 | 123 | 72.0 | 72.3 | 71.2164 | 72.3297 | | |
| | | 125 | 122.1 | 69.1 | 68.9 | 67.6011 | 70.9270 | | |
| | | 150 | 120.5 | 66.2 | 65.6 | 64.0786 | 65.7866 | | |
| 2 | **SHOVEL** | 5 | 113.4 | 90.2 | 90 | 85.9079 | 85.8342 | 2.2164 | 1.7342 |
| | (Wind Speed: 3.2 m/sec) | 25 | 120.9 | 81.9 | 81.6 | 82.7403 | 82.8065 | | |
| | (Temp. : $27^0$C) | 50 | 121.9 | 77.0 | 76.4 | 79.1367 | 76.4520 | | |
| | (Relative humidity: 59 %) | 75 | 122.2 | 73.7 | 72.8 | 75.6010 | 73.3383 | | |
| | | 100 | 121.9 | 70.9 | 72.3 | 72.1155 | 71.4557 | | |
| | | 125 | 121.4 | 68.4 | 69.2 | 68.7010 | 70.2106 | | |
| | | 150 | 120.4 | 65.9 | 66.2 | 65.3498 | 65.7345 | | |
| 3 | **DUMPER** | 5 | 113.6 | 88.6 | 88.5 | 85.2253 | 85.6496 | 2.5810 | 1.3628 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.2 | 79.1 | 78.8 | 81.8944 | 79.3408 | | |
| | (Temp. : $29^0$C) | 50 | 119.8 | 74.9 | 74.3 | 77.9546 | 74.2734 | | |
| | (Relative humidity: 58 %) | 75 | 121.5 | 73 | 72.2 | 74.1525 | 72.7043 | | |
| | | 100 | 122.8 | 71.8 | 72.7 | 70.5321 | 72.1820 | | |
| | | 125 | 120.6 | 67.6 | 68.1 | 66.9308 | 69.4051 | | |
| | | 150 | 115.8 | 61.3 | 61.5 | 63.2595 | 63.0352 | | |
| 4 | **PAYLOADER** | 5 | 111.5 | 86.5 | 86.4 | 84.6968 | 87.5590 | 1.2667 | 0.8597 |
| | (Wind Speed: 3 m/sec) | 25 | 119.5 | 80.5 | 80.2 | 81.1569 | 80.9330 | | |
| | (Temp. : $30^0$C) | 50 | 122.3 | 77.4 | 77.0 | 77.1546 | 76.8171 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 72.5 | 73.3550 | 72.8901 | | |
| | | 100 | 121.0 | 70.0 | 71.0 | 69.6660 | 70.6129 | | |
| | | 125 | 118.6 | 65.6 | 66.2 | 66.0658 | 67.5981 | | |
| | | 150 | 114.2 | 59.7 | 60.3 | 62.5052 | 61.3016 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.4 | 87.4 | 87.3 | 82.6405 | 86.7646 | 2.5208 | 0.7497 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.5 | 78.5 | 78.2 | 79.5557 | 78.8712 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 73.5 | 76.0218 | 73.3736 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 69.7 | 72.6065 | 70.1189 | | |
| | | 100 | 117.3 | 66.3 | 67.4 | 69.2251 | 66.9607 | | |
| | | 125 | 116.6 | 63.6 | 64.6 | 65.9735 | 65.9874 | | |
| | | 150 | 115.6 | 61.1 | 61.9 | 62.8526 | 62.8421 | | |
| 6 | **ROTARY PERCUSSIVE DRILL** | 5 | 119.4 | 94.4 | 94.3 | 85.1592 | 88.8777 | 4.2499 | 2.2341 |
| | (Wind Speed: 2 m/sec) | 25 | 118.4 | 79.4 | 79.1 | 82.0850 | 79.5355 | | |
| | (Temp. : $30^0$C) | 50 | 120.5 | 75.6 | 75.0 | 78.1340 | 75.0565 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.0 | 74.3413 | 72.5141 | | |
| | | 100 | 123.7 | 72.7 | 74.9 | 70.7435 | 72.8151 | | |
| | | 125 | 118.7 | 65.7 | 68.2 | 67.0713 | 67.6814 | | |
| | | 150 | 116.0 | 61.5 | 63.9 | 63.5674 | 63.2179 | | |
| 7 | **ROLL CRUSHER** | 5 | 109.9 | 84.9 | 84.8 | 80.2790 | 88.7834 | 1.9313 | 1.5420 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 78.9 | 76.6041 | 79.3408 | | |
| | (Temp. : $32^0$C) | 50 | 118.6 | 73.7 | 73.3 | 72.7224 | 72.9556 | | |
| | (Relative humidity: 58 %) | 75 | 118.3 | 69.8 | 69.2 | 69.0443 | 69.1767 | | |
| | | 100 | 114.2 | 63.2 | 65.8 | 65.6149 | 65.1828 | | |
| | | 125 | 112.9 | 59.9 | 62.4 | 62.3505 | 62.6327 | | |
| | | 150 | 111.6 | 57.1 | 59.4 | 59.3437 | 59.2337 | | |

Table 5.28: Comparative study between ENM and ANN System based models

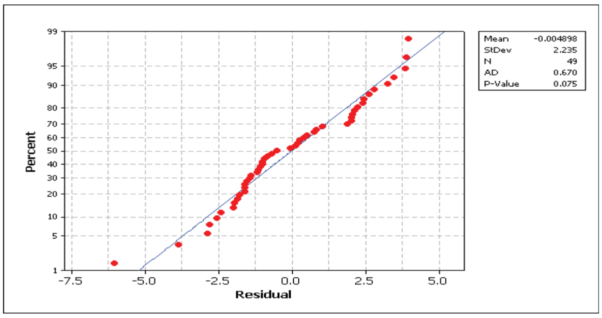
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted ENM in dB(A) | MLP Predicted SPL in dB(A) | RBF Predicted SPL in dB(A) | RMSE error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MLP | RBF |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 92.4 | 90.8209 | 87.7659 | 2.0462 | 1.8122 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 85.0 | 87.0859 | 85.5331 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 80.3 | 83.1724 | 80.5684 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 77.7 | 79.3563 | 76.9886 | | |
| | | 100 | 123.0 | 72.0 | 74.2 | 75.7683 | 74.9197 | | |
| | | 125 | 122.1 | 69.1 | 74.1 | 72.2745 | 74.3933 | | |
| | | 150 | 120.8 | 66.3 | 71.3 | 68.9172 | 71.0808 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 93.3 | 89.6055 | 87.6117 | 2.3853 | 2.2165 |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 84.7 | 86.0359 | 85.3242 | | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 79.6 | 82.2567 | 79.8827 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 75.9 | 78.6338 | 76.0065 | | |
| | | 100 | 122.0 | 71.0 | 72.9 | 75.1359 | 73.9848 | | |
| | | 125 | 121.4 | 68.4 | 72.9 | 71.7581 | 73.4916 | | |
| | | 150 | 120.4 | 65.9 | 70.4 | 68.5133 | 70.5620 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 91.7 | 87.6697 | 88.0508 | 2.3554 | 1.6262 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 82.1 | 84.2089 | 82.8767 | | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 77.5 | 80.3512 | 77.4232 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 75.3 | 76.6100 | 75.4600 | | |
| | | 100 | 122.9 | 71.9 | 73.8 | 73.0293 | 74.8387 | | |
| | | 125 | 120.7 | 67.7 | 72.4 | 69.7127 | 72.4766 | | |
| | | 150 | 115.9 | 61.4 | 65.9 | 66.5952 | 64.0355 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 89.6 | 86.1052 | 88.5459 | 1.7547 | 0.9745 |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 83.3 | 82.3930 | 84.1636 | | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 80.0 | 78.5419 | 80.2279 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 75.5 | 75.0118 | 75.5422 | | |
| | | 100 | 121.0 | 70.0 | 72.3 | 71.5730 | 72.7856 | | |
| | | 125 | 118.6 | 65.6 | 70.4 | 68.2982 | 69.0284 | | |
| | | 150 | 114.3 | 59.8 | 64.1 | 65.1985 | 62.4814 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 90.4 | 82.3431 | 88.4609 | 3.1758 | 1.2935 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 81.2 | 79.1937 | 81.9798 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 76.5 | 75.8484 | 76.3476 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 72.7 | 72.7001 | 73.1636 | | |
| | | 100 | 119.4 | 68.4 | 70.3 | 69.6611 | 70.5026 | | |
| | | 125 | 118.8 | 65.8 | 67.4 | 66.7553 | 69.3622 | | |
| | | 150 | 117.7 | 63.2 | 64.6 | 63.9559 | 66.3928 | | |
| 6 | **ROTARY PERCUSSIVE DRILL** | 5 | 119.4 | 94.4 | 97.3 | 84.5942 | 93.7360 | 5.1004 | 1.5187 |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 82.3 | 81.6873 | 83.3294 | | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 78.2 | 77.9206 | 78.3539 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 75.0 | 74.3739 | 75.2060 | | |
| | | 100 | 123.8 | 72.8 | 74.7 | 70.9013 | 75.4694 | | |
| | | 125 | 118.7 | 65.7 | 70.0 | 67.7657 | 69.1950 | | |
| | | 150 | 116.1 | 61.6 | 65.3 | 64.6720 | 64.2617 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 87.9 | 81.4398 | 88.5990 | 2.9570 | 0.6283 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 81.9 | 78.0562 | 82.6471 | | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 76.4 | 74.6098 | 76.0575 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 72.3 | 71.2840 | 72.5516 | | |
| | | 100 | 117.5 | 66.5 | 68.7 | 68.0667 | 67.8237 | | |
| | | 125 | 116.2 | 63.2 | 65.2 | 64.9592 | 65.4757 | | |
| | | 150 | 114.7 | 60.2 | 62.0 | 61.9723 | 62.8317 | | |

Table 5.29: Comparative study between NORDFORSK and ANN System based models

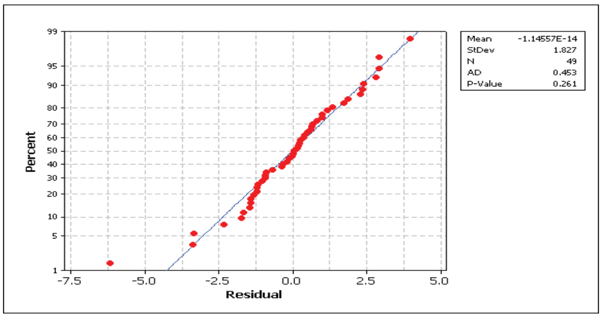
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted NORDFORSK in dB(A) | MLP Predicted SPL in dB(A) | RBF Predicted SPL in dB(A) | RMSE error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MLP | RBF |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 85.7092 | 84.2097 | | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 81.7281 | 83.1233 | | |
| | (Temp. : 28$^0$C) | 50 | 122.7 | 77.8 | 78.0 | 77.1971 | 77.7647 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 75.1 | 72.9095 | 74.7744 | 3.2150 | 2.5540 |
| | | 100 | 123.0 | 72.0 | 71.4 | 68.7258 | 72.0176 | | |
| | | 125 | 122.1 | 69.1 | 68.4 | 64.7747 | 68.9931 | | |
| | | 150 | 120.8 | 66.3 | 65.4 | 61.0618 | 66.5547 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 85.0177 | 84.4617 | | |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 81.2625 | 82.7250 | | |
| | (Temp. : 27$^0$C) | 50 | 122.1 | 77.2 | 77.3 | 76.9669 | 77.2364 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 73.6 | 72.8439 | 73.8356 | 3.0658 | 2.8040 |
| | | 100 | 122.0 | 71.0 | 70.5 | 68.8962 | 71.1880 | | |
| | | 125 | 121.4 | 68.4 | 67.6 | 65.1629 | 68.3584 | | |
| | | 150 | 120.4 | 65.9 | 64.8 | 61.6566 | 66.0393 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 84.2683 | 84.1108 | | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 80.4577 | 79.9611 | | |
| | (Temp. : 29$^0$C) | 50 | 120.0 | 75.1 | 75.3 | 76.0949 | 74.8130 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 73.1 | 72.0437 | 73.3145 | 2.7213 | 2.3713 |
| | | 100 | 122.9 | 71.9 | 71.2 | 68.3160 | 71.9397 | | |
| | | 125 | 120.7 | 67.7 | 67.0 | 64.4702 | 67.7251 | | |
| | | 150 | 115.9 | 61.4 | 60.3 | 60.5459 | 61.2527 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 83.5677 | 84.0971 | | |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 79.7172 | 80.9175 | | |
| | (Temp. : 30$^0$C) | 50 | 122.4 | 77.5 | 77.7 | 75.5832 | 77.5146 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 73.1 | 71.5694 | 73.3933 | 2.2108 | 1.5897 |
| | | 100 | 121.0 | 70.0 | 69.7 | 67.7511 | 70.2303 | | |
| | | 125 | 118.6 | 65.6 | 64.9 | 63.9741 | 65.6850 | | |
| | | 150 | 114.3 | 59.8 | 58.9 | 60.2293 | 60.3594 | | |
| 5 | **ROCK-BREAKER(** | 5 | 112.5 | 87.5 | 88.7 | 80.4504 | 84.0492 | | |
| | Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 77.1148 | 79.7443 | | |
| | (Temp. : 29$^0$C) | 50 | 119.0 | 74.1 | 74.5 | 73.4389 | 73.7086 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 70.6 | 69.9844 | 70.9056 | 3.3559 | 1.8351 |
| | | 100 | 119.4 | 68.4 | 68.0 | 66.8207 | 68.4107 | | |
| | | 125 | 118.8 | 65.8 | 65.1 | 63.8598 | 65.8877 | | |
| | | 150 | 117.7 | 63.2 | 62.2 | 61.1413 | 62.7609 | | |
| 6 | **ROTARY PERCUSSIVE DRILL** | 5 | 119.4 | 94.4 | 95.7 | 82.9080 | 88.2583 | | |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 79.5103 | 80.1946 | | |
| | (Temp. : 30$^0$C) | 50 | 120.8 | 75.9 | 76.1 | 75.4890 | 75.7856 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 71.6362 | 73.0689 | 5.1424 | 2.8372 |
| | | 100 | 123.8 | 72.8 | 72.5 | 68.3350 | 72.6048 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 64.1163 | 65.7864 | | |
| | | 150 | 116.1 | 61.6 | 61.0 | 60.5055 | 61.3910 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 80.3368 | 84.3354 | | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 76.4351 | 79.8768 | | |
| | (Temp. : 32$^0$C) | 50 | 118.7 | 73.8 | 74.1 | 72.5941 | 73.4303 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 69.0310 | 70.1323 | 2.7424 | 0.9582 |
| | | 100 | 117.5 | 66.5 | 66.2 | 65.7372 | 66.1246 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 62.7308 | 63.4277 | | |
| | | 150 | 114.7 | 60.2 | 59.4 | 60.0320 | 60.5510 | | |

Table 5.30: Comparative study between VDI-2720 and ANN System based models

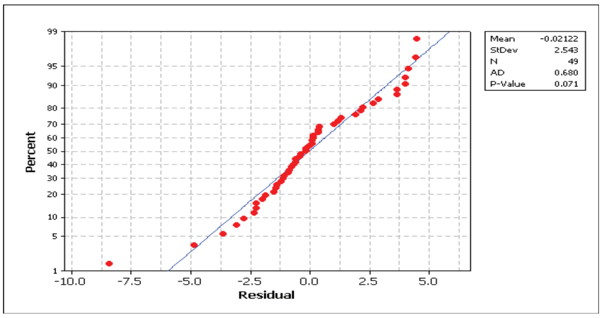
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted VDI-2720 in dB(A) | MLP Predicted SPL in dB(A) | RBF Predicted SPL in dB(A) | RMSE error | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | MLP | RBF |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 90.8237 | 88.1158 | 3.9915 | 3.5990 |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 87.0506 | 84.0923 | | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 78.0 | 83.0910 | 80.5626 | | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 75.2 | 79.4157 | 77.2042 | | |
| | | 100 | 123.0 | 72.0 | 71.4 | 75.8953 | 74.8262 | | |
| | | 125 | 122.1 | 69.1 | 68.4 | 72.5277 | 73.7387 | | |
| | | 150 | 120.8 | 66.3 | 65.4 | 69.2705 | 71.0264 | | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 88.5038 | 88.0149 | 3.1298 | 3.7776 |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 84.8131 | 83.6395 | | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 77.4 | 80.9138 | 80.0476 | | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 73.6 | 77.2905 | 75.8892 | | |
| | | 100 | 122.0 | 71.0 | 70.5 | 73.8898 | 73.7761 | | |
| | | 125 | 121.4 | 68.4 | 67.7 | 70.6859 | 73.2047 | | |
| | | 150 | 120.4 | 65.9 | 64.9 | 67.6416 | 70.5696 | | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 87.7898 | 88.0133 | 3.7174 | 3.1245 |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 84.1431 | 81.6824 | | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 75.3 | 80.1061 | 77.8003 | | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 73.1 | 76.3893 | 75.2730 | | |
| | | 100 | 122.9 | 71.9 | 71.6 | 73.0046 | 74.7188 | | |
| | | 125 | 120.7 | 67.7 | 67.0 | 69.6057 | 72.5346 | | |
| | | 150 | 115.9 | 61.4 | 60.4 | 66.0478 | 63.5175 | | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 86.5594 | 86.6082 | 2.8156 | 2.8626 |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 82.7263 | 81.8801 | | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 77.7 | 78.7466 | 80.3171 | | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 73.1 | 75.0661 | 75.3628 | | |
| | | 100 | 121.0 | 70.0 | 69.7 | 71.5780 | 72.7251 | | |
| | | 125 | 118.6 | 65.6 | 65.0 | 68.1417 | 69.1529 | | |
| | | 150 | 114.3 | 59.8 | 58.9 | 64.6452 | 63.0065 | | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 88.7 | 81.2833 | 87.2560 | 2.9089 | 2.8898 |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 77.7000 | 82.2890 | | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 74.6 | 74.1619 | 76.8694 | | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 70.6 | 71.0264 | 72.8215 | | |
| | | 100 | 119.4 | 68.4 | 68.0 | 68.1628 | 70.7370 | | |
| | | 125 | 118.8 | 65.8 | 65.1 | 65.5617 | 69.5572 | | |
| | | 150 | 117.7 | 63.2 | 62.3 | 63.1500 | 65.5529 | | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 85.0327 | 85.5189 | 4.4057 | 4.6527 |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 81.7605 | 81.5818 | | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 76.1 | 77.7730 | 78.6806 | | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 74.1002 | 74.9997 | | |
| | | 100 | 123.8 | 72.8 | 72.5 | 70.8514 | 75.7136 | | |
| | | 125 | 118.7 | 65.7 | 65.1 | 67.2596 | 69.3560 | | |
| | | 150 | 116.1 | 61.6 | 61.0 | 63.9770 | 63.6409 | | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 82.0788 | 85.2904 | 2.2718 | 2.3381 |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 78.1886 | 81.7892 | | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 74.2 | 74.4487 | 76.6552 | | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 70.9934 | 72.0989 | | |
| | | 100 | 117.5 | 66.5 | 66.2 | 67.7724 | 67.8108 | | |
| | | 125 | 116.2 | 63.2 | 62.6 | 64.7502 | 65.3186 | | |
| | | 150 | 114.7 | 60.2 | 59.4 | 61.9105 | 63.0803 | | |



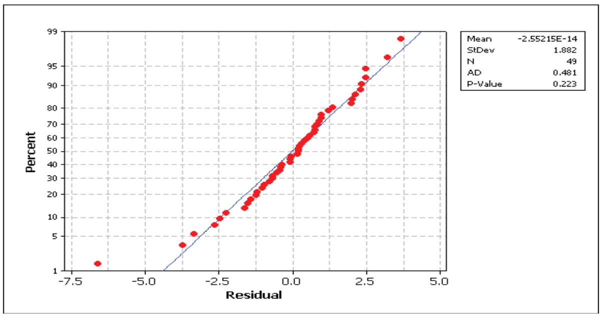

(a)



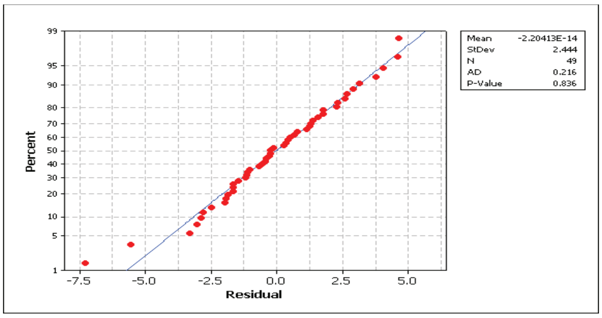

(b)




(c)




(d)

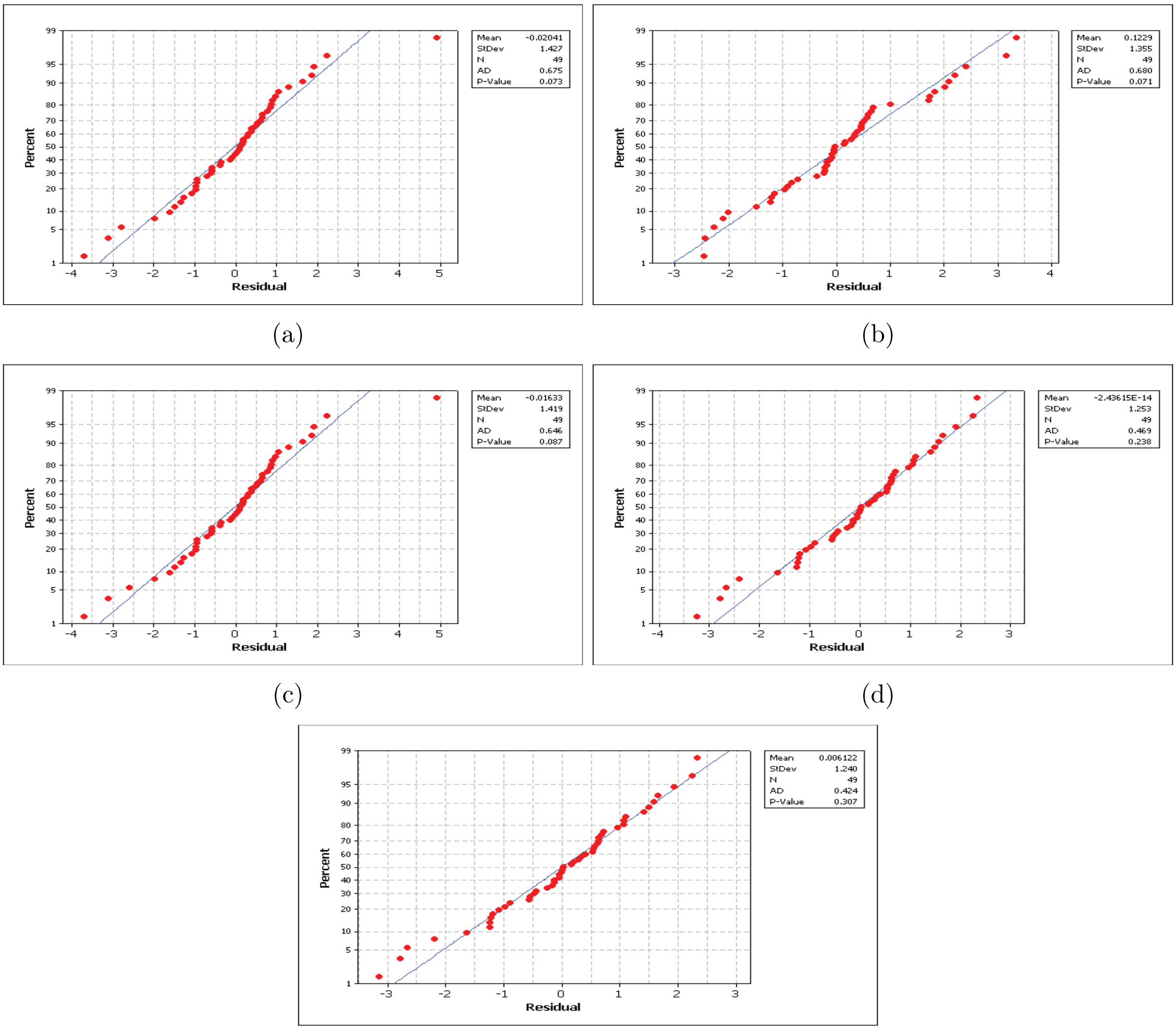



(e)

Figure 5.29: Statistical performance study of MLP model based noise prediction(a)CONCAWE, (b)ISO-9613-2, (c) ENM, (d) NORDFORSK (e) VDI-2720

### 5.3.3 Application of Adaptive Network Based Fuzzy Inference System (ANFIS) for Frequency based Noise Prediction

Frequency based noise prediction was implemented using ANN as discussed in section 5.3.2. This section analyzes implementation of ANFIS for the same problem. ANFIS has been applied for all frequency based noise prediction models viz. ISO-9613-2, CONCAWE, ENM etc. In section 5.2.3, the application of ANFIS for non-frequency model (VDI-2714) was already discussed. Procedure for application of ANFIS for frequency based noise prediction model is similar to non-frequency model VDI-2714. In this study, the ANFIS based on T-S-K fuzzy model was used and the adaptation was made in the rule base of the system.




(a) (b) (c) (d) (e)

Figure 5.30: Statistical performance study of RBF model based noise prediction(a)CONCAWE, (b)ISO-9613-2, (c) ENM, (d) NORDFORSK (e) VDI-2720

The selections of input variables , fuzzification process, rule base and defuzzification are similar to T-S-K fuzzy system as discussed in previous section (5.2.1.7).

The details of implementation is presented in Table 5.31. With this it can be seen that there are 810 rules and each rule is associated with a weight. The weights are initialized to random values at the beginning. Subsequently these weights were updated using LMS algorithm [211]. The weight update algorithm can be represented as

$$e(k) = y(k) \;-\; \hat{y}(k) \tag{5.6}$$

$$w(k+1) = w(k) \;+\; 2\,\alpha\, e(k)\, \psi(k) \tag{5.7}$$

Where k is the time index, $w(k+1)$ refers to the new weights of the system and $w(k)$

Table 5.31: Application of Adaptive Network based Fuzzy Inference System (ANFIS) models for frequency based noise prediction models

| Input parameters | Output Parameter | Frequency Dependent Models | ANFIS | | |
|---|---|---|---|---|---|
| | | | Membership function | Inference Engine | Adaption |
| 1. Distance<br>2. Sound Power Level<br>3. Wind<br>4. Relative Humidity<br>5. Temperature | Sound Pressure Level | CONCAWE<br>ENM<br>ISO-9613-2<br>VDI-2720<br>NORDFORSK | **Inputs**<br>Distance: Six<br>SWL: Five<br>Wind: Three<br>Temperature: Three<br>Relative Humidity: Three<br>**Output**<br>Sound Pressure Level: (No. membership function assigned, as ANFIS structure is similar to T-S-K fuzzy model) | $R_1 = {}^1\mu_{dis} \times {}^1\mu_{SWL}, \times {}^1\mu_{wind} \times {}^1\mu_{temp} \times {}^1\mu_{rh}$<br>.<br>.<br>.<br>.<br>.<br>.<br>.<br>.<br>$R_{810} = {}^6\mu_{dis} \times {}^5\mu_{SWL}, \times {}^3\mu_{wind} \times {}^3\mu_{temp} \times {}^3\mu_{rh}$<br>$w_i$(i=1,...810),<br>where $w_i$ is the weight of the system. Here randomly weights are selected. | No. of rules :<br>Total Number of Rule ($R_i$)= (6×5×3×3×3)=810<br>Output:<br>$\hat{y} = \sum_{i=1}^{810} \frac{R_i \times w_i}{w_i}$<br>Where $\hat{y}$ is the estimated output.<br>**Error updation**: LMS equation was used |

is the existing weight. $w{=}[(w_1, w_2 \quad ...w_{810})]^T$ is the weight vector and $\psi = [(\psi_1,\ \psi_2\ .\ .\ .\psi_{810})]$ is the output of the inference engine.

#### 5.3.3.1 Simulation Result and Discussion

The proposed system models for noise prediction were validated using simulation studies. The studies were carried out by using simulation environment. The system was simulated as per the flowchart of the ANFIS system represented in Fig 5.31. The fuzzy parameters were suitably adjusted to enhance the performance of the designed model. ANFIS system was applied for five frequency dependent models (ISO-9613-2, CONCAWE, ENM etc.). ISO-9613-2 model is discussed first. A set of 224 data points were first generated as per the ISO-9613-2 noise prediction model. For this, the input parameters were Distance, sound power level (SWL), Wind speed, Relative humidity and Temperature. Using these input parameters, SPL was calculated. This data set was the basis for training and evaluating or testing the ANFIS prediction model. Out of the 224 data points, 175 were used as training data and 49 were used as testing data. The ANFIS weights were freezed on completion of the experiment in first part. SPL was predicted using ANFIS for each of these machineries and was compared with the ISO-9613-2 model. For ANFIS, weights were trained using LMS algorithm. The mean square error (MSE) of the ANFIS model for 200 epochs was represented in Fig. 5.32(a) and the performance of the model for 49 testing samples or validation samples was represented in Fig. 5.32(b). The root mean square error (RMSE) was used as the performance index.MSE plot of ANFIS for 200 epochs for CONCAWE model is represented in Fig. 5.33(a) and Fig. 5.33(b) represented performance of ANFIS model for CONCAWE. Similarly Fig. 5.34(a) and 5.34(b) represented performance of ENM, Fig 5.35(a) and 5.35(b) represented for NORDFORSK and Fig 5.36(a) and 5.36(b) represented for VDI-2720 model.

Table 5.32 summarizes the results for noise prediction by proposed models and compares it with standard ISO-9613-2 noise prediction model for all selected opencast machineries. From the table it can be seen that the proposed ANFIS models provided root mean square error of 2.0503 for Dozer. For shovel, the root mean square error was 1.3764, for Dumper, the RMSE was 2.8031, for Payloader, RMSE for ANFIS systems was 1.2121 respectively. The other machineries results were similar to the above result. For rock breaker, root mean square errors was 1.4728, for rotary percussive drill, RMSE was found as 1.8527 and for roll crusher, the RMSE was found as 1.3991 respectively. Comparative results of other frequency based noise prediction model with ANFIS system were represented in Table 5.33 to 5.36. Table 5.33 represented the comparison result of CONCAWE noise prediction model, Table 5.34 represent the result of ENM model,

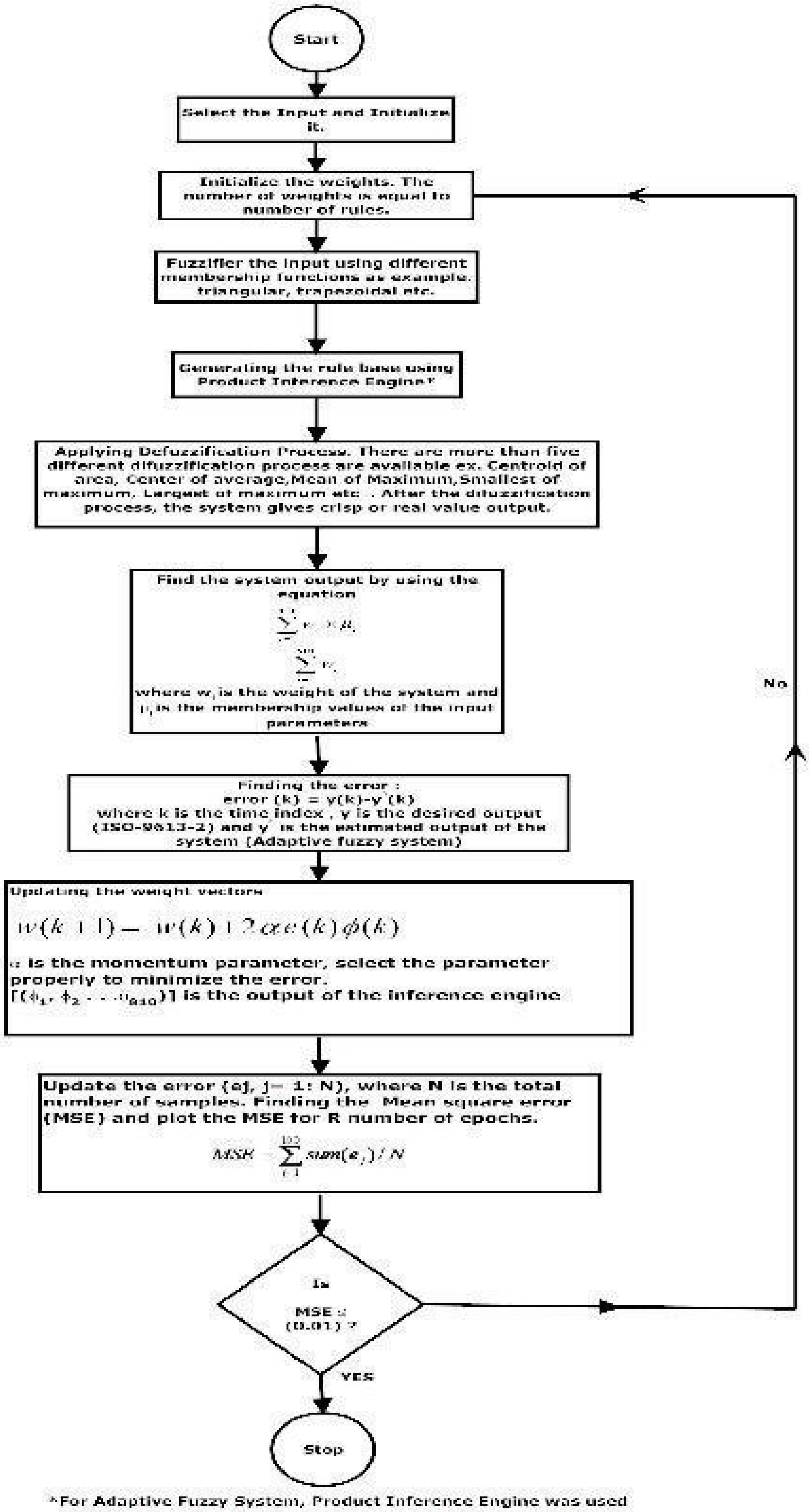
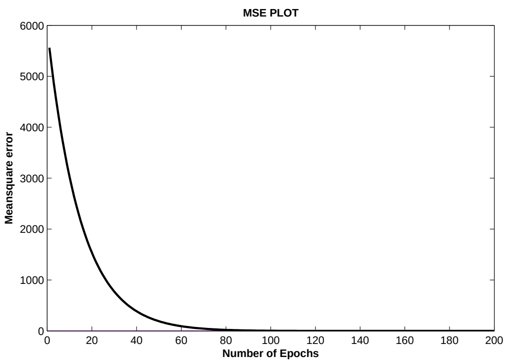
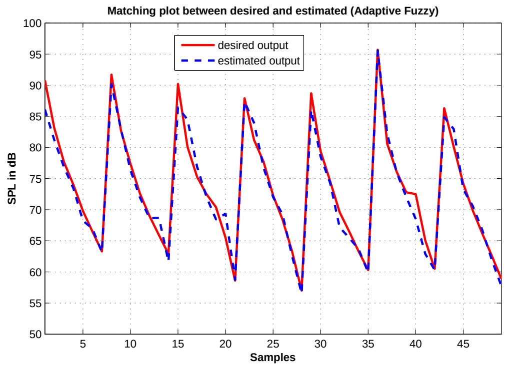



Figure 5.31: Flowchart for ANFIS System

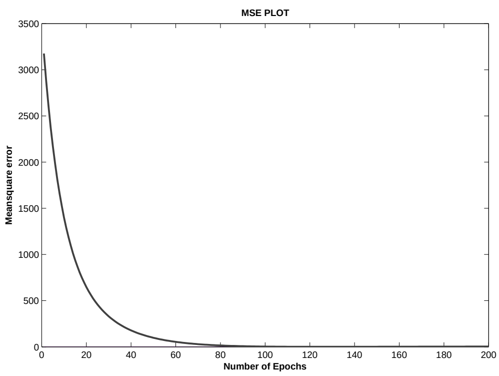



(a)

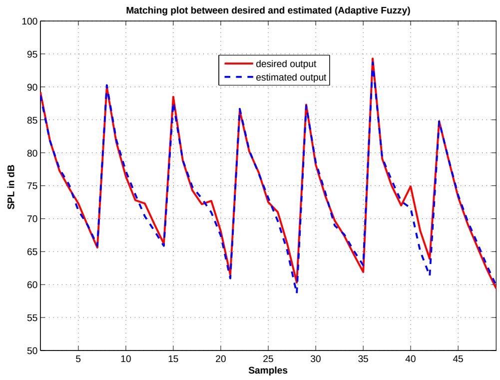



(b)

Figure 5.32: (a) Mean square error plot of ANFIS system for 200 epochs (b) Prediction performance of ANFIS network for 49 samples for ISO-9613-2 noise prediction model

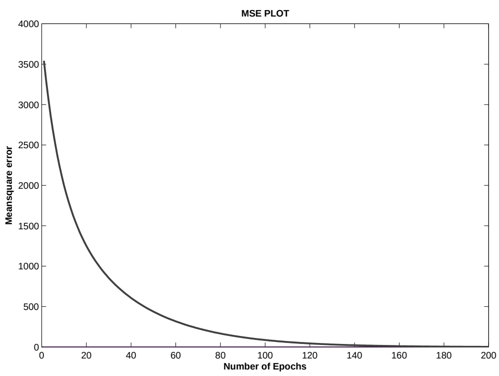



(a)

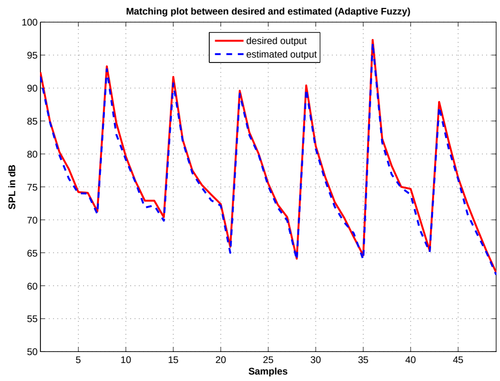



(b)

Figure 5.33: (a) Mean square error plot of ANFIS system for 200 epochs (b) Prediction performance of ANFIS network for 49 samples for CONCAWE noise prediction model

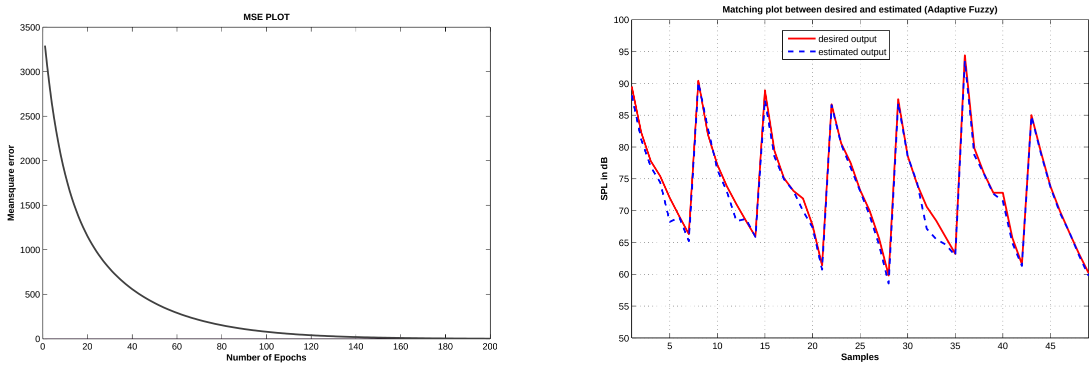



(a)



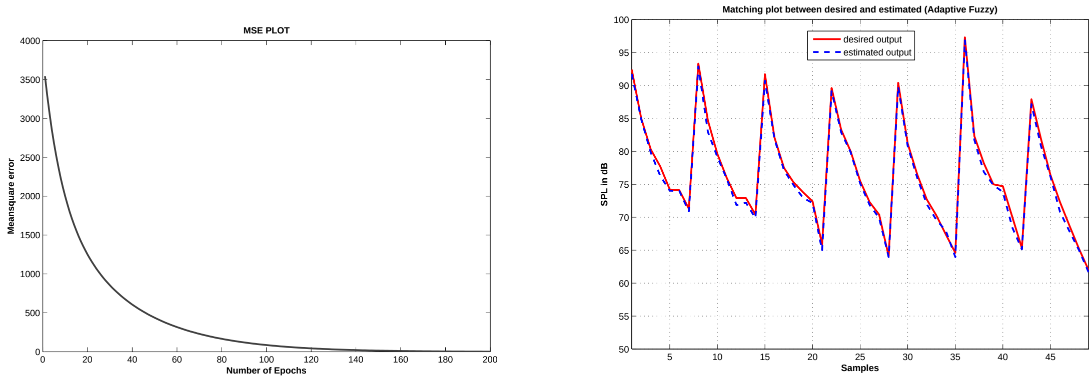

(b)

Figure 5.34: (a) Mean square error plot of ANFIS system for 200 epochs (b) Prediction performance of ANFIS network for 49 samples for ENM noise prediction model




(a) (b)

Figure 5.35: (a) Mean square error plot of ANFIS system for 200 epochs (b) Prediction performance of ANFIS network for 49 samples for NORDFORSK noise prediction model




(a) (b)

Figure 5.36: (a) Mean square error plot of ANFIS system for 200 epochs (b) Prediction performance of ANFIS network for 49 samples for VDI-2720 noise prediction model

Table 5.35 represented the result of NORDFORSK model and Table 5.36 represented the comparison result of VDI-2720 model with ANFIS system based noise prediction models.

Anderson-Darling (AD) normality test results are shown in Figure 5.37 for respective SPL residue. The test is done between the prediction results of ANFIS system and frequency dependent model results. Since p-value of the normality plots are found to be above 0.05, it signifies that the residue follows normal distribution. Small percentage of error proves the suitability of above models for practical engineering applications.

Table 5.32: Comparative study between ISO-9613-2 and ANFIS System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted ISO-9613-2 in dB(A) | ANFIS Predicted SPL in dB(A) | RMSE error |
|---|---|---|---|---|---|---|---|
| | | | | | | | ANFIS |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 86.1085 | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 81.1713 | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 77.7 | 76.8825 | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 74.0 | 73.4198 | 2.0503 |
| | | 100 | 123.0 | 72.0 | 69.8 | 68.2298 | |
| | | 125 | 122.1 | 69.1 | 66.5 | 66.9626 | |
| | | 150 | 120.8 | 66.3 | 63.3 | 63.1897 | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 90.1629 | |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 82.9526 | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 77.4 | 76.3996 | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 72.6 | 71.9780 | 1.3764 |
| | | 100 | 122.0 | 71.0 | 69.0 | 68.6507 | |
| | | 125 | 121.4 | 68.4 | 65.9 | 68.6931 | |
| | | 150 | 120.4 | 65.9 | 62.9 | 61.6653 | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 86.4146 | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 84.4753 | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 75.3 | 76.9335 | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 72.5 | 72.0647 | 2.8031 |
| | | 100 | 122.9 | 71.9 | 70.4 | 68.4483 | |
| | | 125 | 120.7 | 67.7 | 65.5 | 69.3529 | |
| | | 150 | 115.9 | 61.4 | 58.6 | 58.7323 | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 87.3627 | |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 83.9581 | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 77.7 | 76.7608 | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 72.3 | 72.0478 | 1.2121 |
| | | 100 | 121.0 | 70.0 | 68.4 | 69.2419 | |
| | | 125 | 118.6 | 65.6 | 63.3 | 62.5727 | |
| | | 150 | 114.3 | 59.8 | 57.0 | 56.5476 | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 88.7 | 86.0346 | |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 78.5473 | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 74.6 | 74.3004 | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 69.6 | 67.1520 | 1.4728 |
| | | 100 | 119.4 | 68.4 | 66.5 | 65.5004 | |
| | | 125 | 118.8 | 65.8 | 63.3 | 63.6601 | |
| | | 150 | 117.7 | 63.2 | 60.3 | 59.9252 | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 95.5379 | |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 82.2316 | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 76.1 | 76.0297 | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 72.0605 | 1.8527 |
| | | 100 | 123.8 | 72.8 | 72.5 | 68.5047 | |
| | | 125 | 118.7 | 65.7 | 65.1 | 62.9111 | |
| | | 150 | 116.1 | 61.6 | 60.5 | 60.3135 | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 84.8600 | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 82.9662 | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 74.2 | 73.2672 | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 70.6211 | 1.3991 |
| | | 100 | 117.5 | 66.5 | 66.2 | 66.7572 | |
| | | 125 | 116.2 | 63.2 | 62.6 | 61.9483 | |
| | | 150 | 114.7 | 60.2 | 58.9 | 57.7647 | |

Table 5.33: Comparative study between CONCAWE and ANFIS System based models

| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted CONCAWE in dB(A) | ANFIS Predicted SPL in dB(A) | RMSE error ANFIS |
|---|---|---|---|---|---|---|---|
| 1 | **DOZER** (Wind Speed: 2.5 m/sec) (Temp. : $28^0$C) (Relative humidity: 57 %) | 5 | 114.6 | 89.3 | 89.2 | 88.7085 | 0.5111 |
| | | 25 | 121.2 | 82.2 | 81.9 | 81.8713 | |
| | | 50 | 122.7 | 77.8 | 77.3 | 77.5825 | |
| | | 75 | 123.9 | 75.4 | 74.7 | 75.2198 | |
| | | 100 | 123 | 72.0 | 72.3 | 71.2298 | |
| | | 125 | 122.1 | 69.1 | 68.9 | 68.9826 | |
| | | 150 | 120.5 | 66.2 | 65.6 | 65.8897 | |
| 2 | **SHOVEL** (Wind Speed: 3.2 m/sec) (Temp. : $27^0$C) (Relative humidity: 59 %) | 5 | 113.4 | 90.2 | 90 | 90.2629 | 0.9658 |
| | | 25 | 120.9 | 81.9 | 81.6 | 81.9526 | |
| | | 50 | 121.9 | 77.0 | 76.4 | 77.1996 | |
| | | 75 | 122.2 | 73.7 | 72.8 | 73.6780 | |
| | | 100 | 121.9 | 70.9 | 72.3 | 70.3507 | |
| | | 125 | 121.4 | 68.4 | 69.2 | 68.1931 | |
| | | 150 | 120.4 | 65.9 | 66.2 | 65.8653 | |
| 3 | **DUMPER** (Wind Speed: 2.91 m/sec) (Temp. : $29^0$C) (Relative humidity: 58 %) | 5 | 113.6 | 88.6 | 88.5 | 87.6146 | 0.8969 |
| | | 25 | 118.2 | 79.1 | 78.8 | 78.8753 | |
| | | 50 | 119.8 | 74.9 | 74.3 | 74.8335 | |
| | | 75 | 121.5 | 73 | 72.2 | 73.0647 | |
| | | 100 | 122.8 | 71.8 | 72.7 | 70.9483 | |
| | | 125 | 120.6 | 67.6 | 68.1 | 67.4529 | |
| | | 150 | 115.8 | 61.3 | 61.5 | 60.9323 | |
| 4 | **PAYLOADER** (Wind Speed: 3 m/sec) (Temp. : $30^0$C) (Relative humidity: 58 %) | 5 | 111.5 | 86.5 | 86.4 | 86.6627 | 0.9383 |
| | | 25 | 119.5 | 80.5 | 80.2 | 80.3581 | |
| | | 50 | 122.3 | 77.4 | 77.0 | 76.8608 | |
| | | 75 | 121.7 | 73.2 | 72.5 | 73.1478 | |
| | | 100 | 121.0 | 70.0 | 71.0 | 69.6419 | |
| | | 125 | 118.6 | 65.6 | 66.2 | 65.1727 | |
| | | 150 | 114.2 | 59.7 | 60.3 | 58.6476 | |
| 5 | **ROCK-BREAKER** (Wind Speed: 7.1 m/sec) (Temp. : $29^0$C) (Relative humidity: 61 %) | 5 | 112.4 | 87.4 | 87.3 | 87.1346 | 0.5822 |
| | | 25 | 117.5 | 78.5 | 78.2 | 78.5473 | |
| | | 50 | 119.0 | 74.1 | 73.5 | 74.0104 | |
| | | 75 | 119.1 | 70.6 | 69.7 | 68.9520 | |
| | | 100 | 117.3 | 66.3 | 67.4 | 67.6004 | |
| | | 125 | 116.6 | 63.6 | 64.6 | 65.1601 | |
| | | 150 | 115.6 | 61.1 | 61.9 | 62.9252 | |
| 6 | ROTARY PERCUSSIVE DRILL (Wind Speed: 2 m/sec) (Temp. : $30^0$C) (Relative humidity: 59 %) | 5 | 119.4 | 94.4 | 94.3 | 93.7379 | 2.0180 |
| | | 25 | 118.4 | 79.4 | 79.1 | 79.2316 | |
| | | 50 | 120.5 | 75.6 | 75.0 | 75.8197 | |
| | | 75 | 121.3 | 72.8 | 72.0 | 72.6405 | |
| | | 100 | 123.7 | 72.7 | 74.9 | 71.6047 | |
| | | 125 | 118.7 | 65.7 | 68.2 | 65.1111 | |
| | | 150 | 116.0 | 61.5 | 63.9 | 61.3135 | |
| 7 | **ROLL CRUSHER** (Wind Speed: 7 m/sec) (Temp. : $32^0$C) (Relative humidity: 58 %) | 5 | 109.9 | 84.9 | 84.8 | 84.7600 | 0.3947 |
| | | 25 | 118.2 | 79.2 | 78.9 | 78.9662 | |
| | | 50 | 118.6 | 73.7 | 73.3 | 73.5672 | |
| | | 75 | 118.3 | 69.8 | 69.2 | 69.6211 | |
| | | 100 | 114.2 | 63.2 | 65.8 | 66.3572 | |
| | | 125 | 112.9 | 59.9 | 62.4 | 62.9563 | |
| | | 150 | 111.6 | 57.1 | 59.4 | 59.8647 | |

Table 5.34: Comparative study between ENM and ANFIS System based models

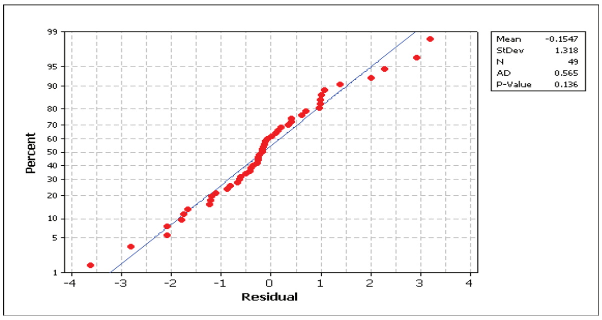
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted ENM in dB(A) | ANFIS Predicted SPL in dB(A) | RMSE error |
|---|---|---|---|---|---|---|---|
| | | | | | | | ANFIS |
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 92.4 | 91.7085 | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 85.0 | 84.8713 | |
| | (Temp. : $28^{0}$C) | 50 | 122.7 | 77.8 | 80.3 | 79.8252 | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 77.7 | 76.2598 | 0.6552 |
| | | 100 | 123.0 | 72.0 | 74.2 | 74.0298 | |
| | | 125 | 122.1 | 69.1 | 74.1 | 73.9826 | |
| | | 150 | 120.8 | 66.3 | 71.3 | 70.8897 | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 93.3 | 92.8627 | |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 84.7 | 82.9525 | |
| | (Temp. : $27^{0}$C) | 50 | 122.1 | 77.2 | 79.6 | 79.1196 | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 75.9 | 75.7780 | 0.8765 |
| | | 100 | 122.0 | 71.0 | 72.9 | 71.8507 | |
| | | 125 | 121.4 | 68.4 | 72.9 | 72.1931 | |
| | | 150 | 120.4 | 65.9 | 70.4 | 69.8653 | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 91.7 | 90.7146 | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 82.1 | 81.8753 | |
| | (Temp. : $29^{0}$C) | 50 | 120.0 | 75.1 | 77.5 | 77.1345 | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 75.3 | 74.8877 | 0.6496 |
| | | 100 | 122.9 | 71.9 | 73.8 | 72.9483 | |
| | | 125 | 120.7 | 67.7 | 72.4 | 72.1519 | |
| | | 150 | 115.9 | 61.4 | 65.9 | 64.9823 | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 89.6 | 89.1327 | |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 83.3 | 82.8981 | |
| | (Temp. : $30^{0}$C) | 50 | 122.4 | 77.5 | 80.0 | 79.8408 | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 75.5 | 75.1178 | 0.3824 |
| | | 100 | 121.0 | 70.0 | 72.3 | 71.8619 | |
| | | 125 | 118.6 | 65.6 | 70.4 | 69.8927 | |
| | | 150 | 114.3 | 59.8 | 64.1 | 63.9486 | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 90.4 | 89.8216 | |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 81.2 | 80.7873 | |
| | (Temp. : $29^{0}$C) | 50 | 119.0 | 74.1 | 76.5 | 75.9802 | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 72.7 | 71.9931 | 0.5956 |
| | | 100 | 119.4 | 68.4 | 70.3 | 69.6054 | |
| | | 125 | 118.8 | 65.8 | 67.4 | 67.9681 | |
| | | 150 | 117.7 | 63.2 | 64.6 | 63.9652 | |
| 6 | **ROTARY PERCUSSIVE DRILL** | 5 | 119.4 | 94.4 | 97.3 | 96.8379 | |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 82.3 | 81.7316 | |
| | (Temp. : $30^{0}$C) | 50 | 120.8 | 75.9 | 78.2 | 76.8824 | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 75.0 | 74.8805 | 0.8940 |
| | | 100 | 123.8 | 72.8 | 74.7 | 73.8347 | |
| | | 125 | 118.7 | 65.7 | 70.0 | 68.4111 | |
| | | 150 | 116.1 | 61.6 | 65.3 | 65.1135 | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 87.9 | 87.1500 | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 81.9 | 80.8262 | |
| | (Temp. : $32^{0}$C) | 50 | 118.7 | 73.8 | 76.4 | 76.1672 | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 72.3 | 70.8211 | 0.8304 |
| | | 100 | 117.5 | 66.5 | 68.7 | 67.8562 | |
| | | 125 | 116.2 | 63.2 | 65.2 | 64.9865 | |
| | | 150 | 114.7 | 60.2 | 62.0 | 61.6647 | |

Table 5.35: Comparative study between NORDFORSK and ANFIS System based models

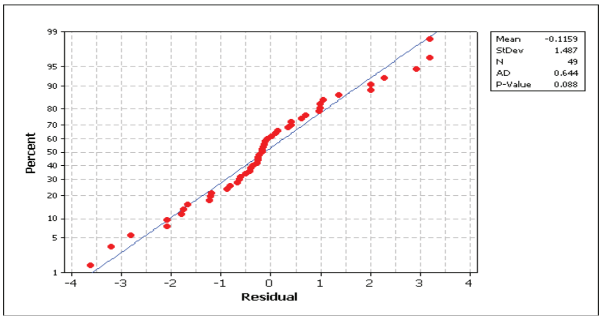
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted NORDFORSK in dB(A) | ANFIS Predicted SPL in dB(A) | RMSE error ANFIS |
|---|---|---|---|---|---|---|---|
| 1 | **DOZER** | 5 | 114.5 | 89.5 | 90.8 | 88.1085 | |
| | (Wind Speed: 2.5 m/sec) | 25 | 121.3 | 82.3 | 83.1 | 81.1713 | |
| | (Temp. : $28^0$C) | 50 | 122.7 | 77.8 | 78.0 | 76.8825 | |
| | (Relative humidity: 57 %) | 75 | 123.9 | 75.4 | 75.1 | 74.4198 | 1.8161 |
| | | 100 | 123.0 | 72.0 | 71.4 | 68.2298 | |
| | | 125 | 122.1 | 69.1 | 68.4 | 68.9626 | |
| | | 150 | 120.8 | 66.3 | 65.4 | 65.1897 | |
| 2 | **SHOVEL** | 5 | 115.4 | 90.4 | 91.7 | 90.1629 | |
| | (Wind Speed: 3.2 m/sec) | 25 | 121.0 | 82.0 | 82.7 | 82.9526 | |
| | (Temp. : $27^0$C) | 50 | 122.1 | 77.2 | 77.3 | 76.3996 | |
| | (Relative humidity: 59 %) | 75 | 122.3 | 73.8 | 73.6 | 72.9780 | 1.2290 |
| | | 100 | 122.0 | 71.0 | 70.5 | 68.3507 | |
| | | 125 | 121.4 | 68.4 | 67.6 | 68.6931 | |
| | | 150 | 120.4 | 65.9 | 64.8 | 65.8653 | |
| 3 | **DUMPER** | 5 | 113.9 | 88.9 | 90.2 | 87.4146 | |
| | (Wind Speed: 2.91 m/sec) | 25 | 118.4 | 79.4 | 80.1 | 78.4753 | |
| | (Temp. : $29^0$C) | 50 | 120.0 | 75.1 | 75.3 | 74.9335 | |
| | (Relative humidity: 58 %) | 75 | 121.6 | 73.1 | 73.1 | 73.0647 | 1.3316 |
| | | 100 | 122.9 | 71.9 | 71.2 | 69.9483 | |
| | | 125 | 120.7 | 67.7 | 67.0 | 67.3529 | |
| | | 150 | 115.9 | 61.4 | 60.3 | 60.7323 | |
| 4 | **PAYLOADER** | 5 | 111.7 | 86.7 | 87.9 | 86.5627 | |
| | (Wind Speed: 3 m/sec) | 25 | 119.6 | 80.6 | 81.2 | 80.4581 | |
| | (Temp. : $30^0$C) | 50 | 122.4 | 77.5 | 77.7 | 76.7608 | |
| | (Relative humidity: 58 %) | 75 | 121.7 | 73.2 | 73.1 | 73.0478 | 0.7236 |
| | | 100 | 121.0 | 70.0 | 69.7 | 69.2419 | |
| | | 125 | 118.6 | 65.6 | 64.9 | 64.5727 | |
| | | 150 | 114.3 | 59.8 | 58.9 | 58.5476 | |
| 5 | **ROCK-BREAKER** | 5 | 112.5 | 87.5 | 88.7 | 86.9346 | |
| | (Wind Speed: 7.1 m/sec) | 25 | 117.6 | 78.6 | 79.4 | 78.5473 | |
| | (Temp. : $29^0$C) | 50 | 119.0 | 74.1 | 74.5 | 74.3004 | |
| | (Relative humidity: 61 %) | 75 | 119.1 | 70.6 | 70.6 | 67.1520 | 1.8024 |
| | | 100 | 119.4 | 68.4 | 68.0 | 65.5004 | |
| | | 125 | 118.8 | 65.8 | 65.1 | 64.6601 | |
| | | 150 | 117.7 | 63.2 | 62.2 | 62.9252 | |
| 6 | ROTARY PERCUSSIVE DRILL | 5 | 119.4 | 94.4 | 95.7 | 93.5379 | |
| | (Wind Speed: 2 m/sec) | 25 | 118.8 | 79.8 | 80.6 | 78.7316 | |
| | (Temp. : $30^0$C) | 50 | 120.8 | 75.9 | 76.1 | 75.8297 | |
| | (Relative humidity: 59 %) | 75 | 121.3 | 72.8 | 72.8 | 72.6605 | 1.1578 |
| | | 100 | 123.8 | 72.8 | 72.5 | 71.5047 | |
| | | 125 | 118.7 | 65.7 | 65.1 | 64.9111 | |
| | | 150 | 116.1 | 61.6 | 61.0 | 61.3135 | |
| 7 | **ROLL CRUSHER** | 5 | 110.0 | 85.0 | 86.3 | 84.8600 | |
| | (Wind Speed: 7 m/sec) | 25 | 118.2 | 79.2 | 80.1 | 78.9662 | |
| | (Temp. : $32^0$C) | 50 | 118.7 | 73.8 | 74.1 | 73.6672 | |
| | (Relative humidity: 58 %) | 75 | 118.4 | 69.9 | 69.9 | 69.6211 | 0.7565 |
| | | 100 | 117.5 | 66.5 | 66.2 | 66.5572 | |
| | | 125 | 116.2 | 63.2 | 62.6 | 62.9483 | |
| | | 150 | 114.7 | 60.2 | 59.4 | 59.7647 | |

Table 5.36: Comparative study between VDI-2720 and ANFIS System based models

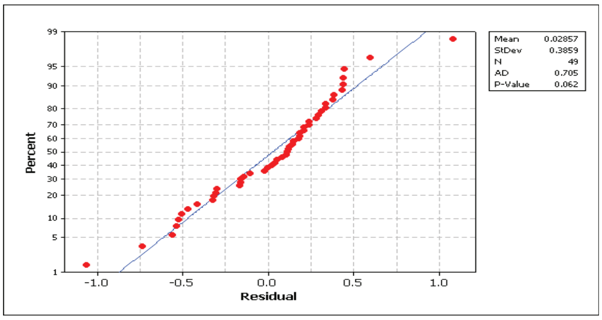
| Sl. No. | Machineries | Distance in meter | SWL in dB (A) | Measured SPL in dB(A) | Predicted VDI-2720 in dB(A) | ANFIS Predicted SPL in dB(A) | RMSE error ANFIS |
|---|---|---|---|---|---|---|---|
| 1 | **DOZER** (Wind Speed: 2.5 m/sec) (Temp. : $28^0$C) (Relative humidity: 57 %) | 5 | 114.5 | 89.5 | 90.8 | 88.1085 | 1.8161 |
| | | 25 | 121.3 | 82.3 | 83.1 | 81.1713 | |
| | | 50 | 122.7 | 77.8 | 78.0 | 76.8825 | |
| | | 75 | 123.9 | 75.4 | 75.2 | 74.4198 | |
| | | 100 | 123.0 | 72.0 | 71.4 | 68.2298 | |
| | | 125 | 122.1 | 69.1 | 68.4 | 68.9626 | |
| | | 150 | 120.8 | 66.3 | 65.4 | 65.1897 | |
| 2 | **SHOVEL** (Wind Speed: 3.2 m/sec) (Temp. : $27^0$C) (Relative humidity: 59 %) | 5 | 115.4 | 90.4 | 91.7 | 90.1629 | 1.2290 |
| | | 25 | 121.0 | 82.0 | 82.7 | 82.9526 | |
| | | 50 | 122.1 | 77.2 | 77.4 | 76.3996 | |
| | | 75 | 122.3 | 73.8 | 73.6 | 72.9780 | |
| | | 100 | 122.0 | 71.0 | 70.5 | 68.3507 | |
| | | 125 | 121.4 | 68.4 | 67.7 | 68.6931 | |
| | | 150 | 120.4 | 65.9 | 64.9 | 65.8653 | |
| 3 | **DUMPER** (Wind Speed: 2.91 m/sec) (Temp. : $29^0$C) (Relative humidity: 58 %) | 5 | 113.9 | 88.9 | 90.2 | 87.4146 | 1.3316 |
| | | 25 | 118.4 | 79.4 | 80.1 | 78.4753 | |
| | | 50 | 120.0 | 75.1 | 75.3 | 74.9335 | |
| | | 75 | 121.6 | 73.1 | 73.1 | 73.0647 | |
| | | 100 | 122.9 | 71.9 | 71.6 | 69.9483 | |
| | | 125 | 120.7 | 67.7 | 67.0 | 67.3529 | |
| | | 150 | 115.9 | 61.4 | 60.4 | 60.7323 | |
| 4 | **PAYLOADER** (Wind Speed: 3 m/sec) (Temp. : $30^0$C) (Relative humidity: 58 %) | 5 | 111.7 | 86.7 | 87.9 | 86.5627 | 0.7236 |
| | | 25 | 119.6 | 80.6 | 81.2 | 80.4581 | |
| | | 50 | 122.4 | 77.5 | 77.7 | 76.7608 | |
| | | 75 | 121.7 | 73.2 | 73.1 | 73.0478 | |
| | | 100 | 121.0 | 70.0 | 69.7 | 69.2419 | |
| | | 125 | 118.6 | 65.6 | 65.0 | 64.5727 | |
| | | 150 | 114.3 | 59.8 | 58.9 | 58.5476 | |
| 5 | **ROCK-BREAKER** (Wind Speed: 7.1 m/sec) (Temp. : $29^0$C) (Relative humidity: 61 %) | 5 | 112.5 | 87.5 | 88.7 | 86.9346 | 1.8024 |
| | | 25 | 117.6 | 78.6 | 79.4 | 78.5473 | |
| | | 50 | 119.0 | 74.1 | 74.6 | 74.3004 | |
| | | 75 | 119.1 | 70.6 | 70.6 | 67.1520 | |
| | | 100 | 119.4 | 68.4 | 68.0 | 65.5004 | |
| | | 125 | 118.8 | 65.8 | 65.1 | 64.6601 | |
| | | 150 | 117.7 | 63.2 | 62.3 | 62.9252 | |
| 6 | ROTARY PERCUSSIVE DRILL (Wind Speed: 2 m/sec) (Temp. : $30^0$C) (Relative humidity: 59 %) | 5 | 119.4 | 94.4 | 95.7 | 93.5379 | 1.1578 |
| | | 25 | 118.8 | 79.8 | 80.6 | 78.7316 | |
| | | 50 | 120.8 | 75.9 | 76.1 | 75.8297 | |
| | | 75 | 121.3 | 72.8 | 72.8 | 72.6605 | |
| | | 100 | 123.8 | 72.8 | 72.5 | 71.5047 | |
| | | 125 | 118.7 | 65.7 | 65.1 | 64.9111 | |
| | | 150 | 116.1 | 61.6 | 61.0 | 61.3135 | |
| 7 | **ROLL CRUSHER** (Wind Speed: 7 m/sec) (Temp. : $32^0$C) (Relative humidity: 58 %) | 5 | 110.0 | 85.0 | 86.3 | 84.8600 | 0.7565 |
| | | 25 | 118.2 | 79.2 | 80.1 | 78.9662 | |
| | | 50 | 118.7 | 73.8 | 74.2 | 73.6672 | |
| | | 75 | 118.4 | 69.9 | 69.9 | 69.6211 | |
| | | 100 | 117.5 | 66.5 | 66.2 | 66.5572 | |
| | | 125 | 116.2 | 63.2 | 62.6 | 62.9483 | |
| | | 150 | 114.7 | 60.2 | 59.4 | 59.7647 | |



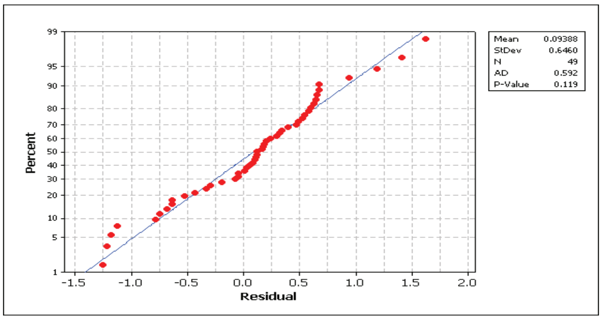

(a)



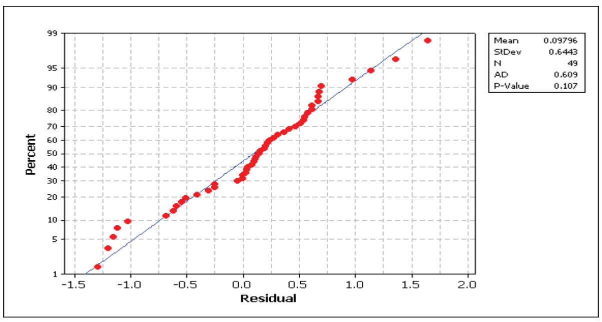

(b)




(c)




(d)




(e)

Figure 5.37: Statistical performance study of ANFIS model based noise prediction(a)CONCAWE, (b)ISO-9613-2, (c) ENM, (d) NORDFORSK (e) VDI-2720

## 5.4 Conclusion

This chapter introduced the idea of designing noise prediction model for opencast mining machineries using Mamdani, T-S-K, ANFIS fuzzy inference systems, MLP and RBF architecture.Different soft computing techniques viz. Fuzzy Inference Systems, Multilayer Perceptron (MLP), Radial Basis Function Network (RBFN) and Adaptive Network based Fuzzy Inference System (ANFIS) were applied for development of non-frequency noise prediction model using VDI-2714. From the simulation result, it is observed that ANFIS gives better noise prediction results as compared to other soft-computing techniques, as it takes very less CPU time (0.0625 sec.) and can be easily implemented in hardware. However, it can be noticed that the other techniques like Fuzzy Logic System, MLP, and RBFN can be applied for non-frequency based noise prediction models. Also Soft-computing techniques viz. Fuzzy Inference Systems, MLP, RBFN and ANFIS were successfully applied for development of frequency dependent models. Soft-computing models were applied to CONCAWE, ISO-9613, ENM etc. From the comparison of all soft-computing models, Radial Basis Function Network and ANFIS results match closely with the mathematical models with minimum Root Mean Square Error (RMSE).Comparing the different techinques of soft computing models for both frequency and non-frequency based noise situations, it was found that ANFIS provides better noise prediction results compared to both frequency and non-frequency based noise prediction models with lower RMSE.

From the simulation result, it was seen that the fuzzy and ANN system provided overestimate and underestimate of the parameters and there is no consistency with respect to this with the input range. However, RBF system provided underestimate when any of the inputs are at the extreme values and it provided overestimate for other ranges of input. This can be attributed to the result that RBF systems are good local approximator [180], whereas Neural Networks [176] and Fuzzy Systems were global approximator [158].

# CHAPTER 6

# NOISE-INDUCED HEARING LOSS (NIHL) MODELING USING FUZZY SYSTEM IN MINING INDUSTRY

## 6.1 Introduction

At the present time, owing to the improvements in technology through superior energy competence, higher labor output, continuous production methods, and operating flexibility, automation has also advanced rapidly in open and underground pits together with mineral processing plants. In parallel to this improvement, sources of noise and ambient noise at work place in the mining industry have increased significantly. With increased mechanization, the problem of noise has got accentuated in opencast mines. Prolonged exposure of miners to the high levels of noise can cause noise-induced hearing loss besides several non-auditory health effects. In general, noise can be described in terms of intensity (perceived as loudness) and frequency. Both the intensity and the duration of noise exposure determine the potential for damage to the hair cells of the inner ear. Therefore, exposure to excessive noise is the major avoidable cause of permanent hearing impairment. Noise-induced hearing loss (NIHL), can be defined as an impairment of hearing, resulting from exposure to excessive noise that manifests over a number of years and results in bilateral and symmetrical impairment of hearing. In mining industry, all most all the opencast mining machineries produce noise levels exceeding the permissible level (90dBA) and the workers are exposed to high noise levels that can cause hearing impairment and other associated health hazards [2, 43, 74].

Hearing loss can impair the quality of life through a reduction in the ability to communicate with each other. Overall, it affects the general health of the human beings in accordance with the World Health Organization's (WHO) definition of health [4, 5].

Hearing loss (HL) can be defined as “the decibel difference between a patient’s thresholds of audibility and that for a person having normal hearing at a given frequency” [6]. In mining industry, hearing loss or hearing damage is considered as a serious health problem, as reported by various health organizations like the U.S. Environmental Protection Agency (USEPA), the National Institute for Occupational Safety and Health (NIOSH) and the WHO etc. In 1976, a study carried out by the National Institute for Occupational Safety and Health, for coal mining concluded that the coal miners had health conditions worse than the national mean and the hearing damage to coal miners were serious [7].

Few studies on hearing loss have been carried out in the mining industry in India and abroad are previously discussed in Chapter 2. In 1997, Prince et al. reported that the hearing loss is significant at 90 dB (A) at 2-4 kHz for very long (40 years)exposure. They also observed that the hearing loss is dependent on the exposure time, frequency and the noise level [32]. Amedofu studied the hearing loss of the African gold mine workers and found similar results. According to his study, 51% of the worker population, those exposed in the noise level of 85dB had the noise induced hearing loss. He also reported that the noise induced hearing loss (NIHL) increased as a function of age at 4 kHz with increase in the duration of exposure [65]. The term ‘Hearing sensitivity’ is defined as the threshold of hearing at different frequencies. In case of human being, the hearing sensitivity is dip in the range of 2-5k Hz and peaks in the range of 3.5-4 kHz [26]. Hence, it can be inferred that NIHL is a function of noise exposure, frequency and exposure time. Fig. 6.1 represents the audiogram analysis of human ear.

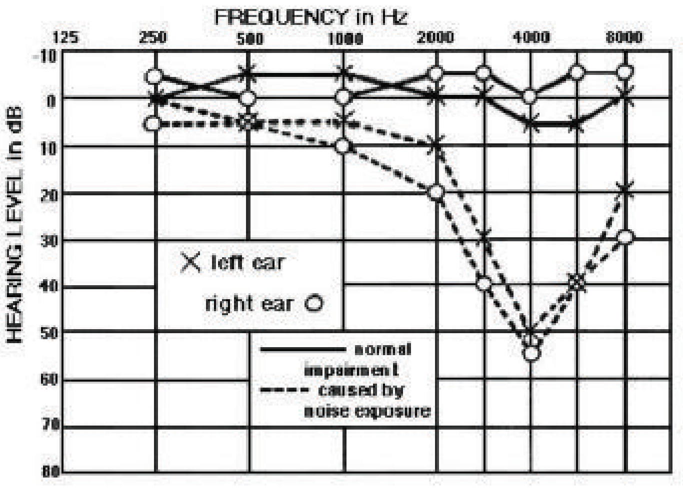



Figure 6.1: Audiogram of normal ears and impaired ears [26].

The above cause-effect relationships obtained by the audiometric testing were reported in the surveys, but the data assembled through surveys or knowledge given by human experts is often imprecise or speculative due to linguistic relationship between hearing loss and its dependent parameters. For example, noise level, frequency, exposure time and hearing loss may be represented by the words (low, medium, high, very high, extreme, extremely high), (very low, low, medium, high, very high, extremely high),(very short, short, medium, long, very long, extreme) and (not significant , slight, mild, mild, severe, extreme) respectively. These linguistic variables cannot be precisely measured and inherently contain imprecision, uncertainty and partial truth. This imprecision, vagueness can be approximate by fuzzy logic system as proposed by Zadeh in 1965 [142]. He defined that, by relying on the use of linguistic variables and fuzzy algorithms, the approach provides an approximate and yet effective means of describing the behavior of systems, which are too complex or too ill defined to admit by precise mathematical analysis [154]. It is difficult to make a mathematical or statistical model for hearing loss by consideration of the above relationship, because the model will incur high computational cost [32]. Therefore, fuzzy logic seems to be the natural choice for developing a model to study the noise induced hearing loss, which is an output of noise level, frequency and years of exposure.

## 6.2 Application of Fuzzy System for Noise Induced Hearing Loss Prediction

In this work, fuzzy logic systems were applied to predict noise induced hearing loss of miners with different frequencies, different exposure time (in years) with different noise level. Soft computing models e.g. ANN, RBFN, ANFIS etc are required large number of training samples for giving better performance, but the Fuzzy logic system is independent of the number of samples and provides better performance with less number of data sets. As the availability of data was less, hence other soft computing models were not applied. This chapter discusses the applications of fuzzy inference systems for noise induced hearing loss prediction. Two types of Fuzzy systems, T-S-K and Mamdani fuzzy inference systems were used.

### 6.2.1 TSK Fuzzy model for Noise Induced Hearing loss Prediction

In the present study, an attempt was made to use sugeno fuzzy model to predict or estimate the noise induced hearing loss given noise level, frequency and the years of exposure as input parameters. With the availability of a set of measured data, an input and output of the fuzzy system will be able to predict the output given any input even if a specific input condition has not been covered in building stage. Figure.6.2 represents the architecture of the TSK fuzzy expert system. As maintained in the figure, the inputs, noise level, frequency and exposure time are taken as X, Y and Z respectively. In the first step, the three crisp inputs are being fuzzified through triangular membership function. Following the fuzzifier, product inference was applied. Since there are three inputs and each input has six possible fuzzy sets, the system can have $6^3$= 216 rules, each corresponding to one of each fuzzy set. The coefficients $a_1$, $b_1$, $c_1$, $d_1$ ...... $a_{216}$, $b_{216}$, $c_{216}$, $d_{216}$ are appropriately selected so as to provide best possible accurate result. After the generation of rule-base, the output would be produced by applying the centroid defuzzification method as mentioned in section 4.2.4, Chapter 4. The model is a MISO model. The methodology for the development of the noise induced hearing loss fuzzy (TSK) model involves the following steps:

1. Selection of input and output variables;
2. Selection of membership functions for input and output variables;
3. Formation of linguistic rule base
4. Defuzzification
5. Parameter optimization

**Step 1: Selection of input and output variables**

The first step in system modeling is the identification of input and output variables called the system's variables. Only those inputs that affect the output largely have been selected. The most important input variables are noise level, year of exposure and frequency. Inclusion of more number of inputs to the system requires more number of rules and hence the complexity increases. The universe of discourse is also decided based on the physical nature of the problem. In the selection procedure, the above-mentioned inputs and the output are also taken in the form of linguistic format that displays an important role in the application of fuzzy logic. For example, noise level ={low, medium, high, very high, extreme, extremely high}, frequency={very low, low, medium, high, very high, extremely high} and exposure time= {very short, short, medium, long, very long, extreme}.The output variables are similarly divided into hearing loss={not significant, slight, mild, marked, severe, extreme}. Table 6.1 shows the linguistic variables, their linguistic value, and associated fuzzy intervals.

**Step 2: Selection of membership functions for input and output variables**

Each input has six triangular membership functions as discussed in Table 4.2, Chapter 4. The membership function of input parameters are represented from Figure 6.3 to 6.5.

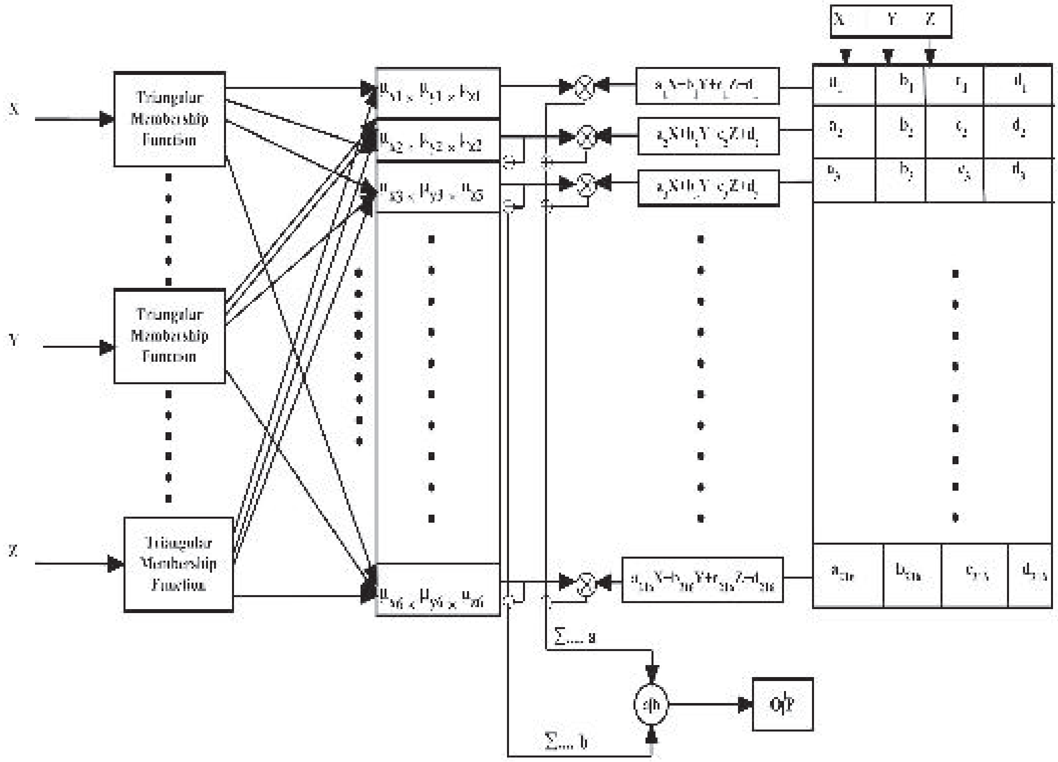


Figure 6.2: System model architecture.

Table 6.1: Inputs and output with their fuzzy and fuzzy intervals

| S. No. | System's variable | Linguistic variables | Linguistic values | Fuzzy interval |
|---|---|---|---|---|
| 1 | Inputs | Noise level | Low | 80-90 dB |
| | | | Medium | 85-95 dB |
| | | | High | 90-100 dB |
| | | | Very high | 95-105 dB |
| | | | Extreme | 100-110 dB |
| | | | Extremely high | 105-115 dB |
| 2 | | Frequency | Very low | 500-1500 Hz |
| | | | Low | 1000-3000 Hz |
| | | | Medium | 2000-4000 Hz |
| | | | High | 3000-5000 Hz |
| | | | Very high | 4500-6500 Hz |
| | | | Extremely high | 6000-8000 Hz |
| 3 | | Exposure time (years) | Very short | 0-6 years |
| | | | Short | 5-11 years |
| | | | Medium | 10-25 years |
| | | | Long | 20-35 years |
| | | | Very long | 30-40 years |
| | | | Extreme | 35-45 years |
| 4 | Output | Hearing loss | Not significant | 0 to -25 dB |
| | | | Slight | -20 to -40 dB |
| | | | Mild | -35 to -55 dB |
| | | | Marked | -50 to -70 dB |
| | | | Severe | -65 to -85 dB |
| | | | Extreme | -80 to -90 dB |

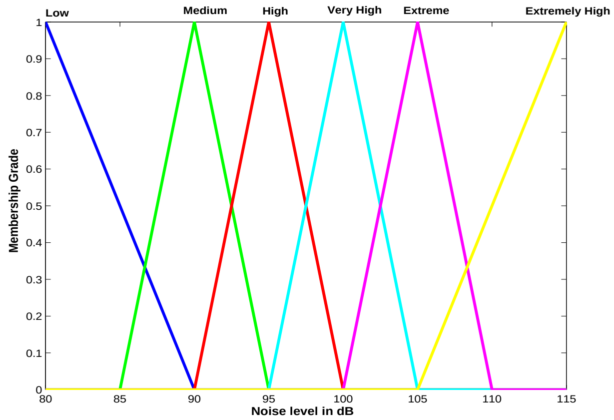



Figure 6.3: Membership functions for noise levels.

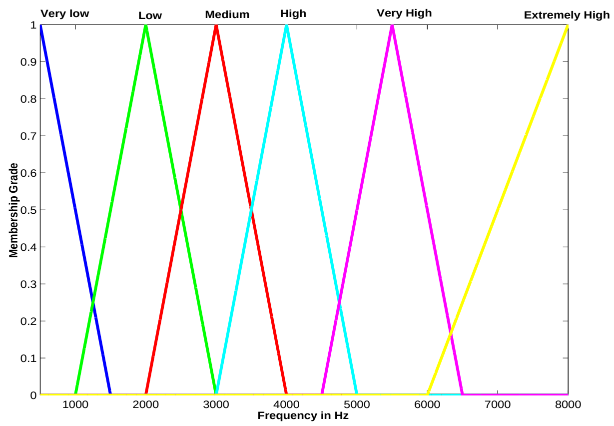



Figure 6.4: Membership functions for frequency.

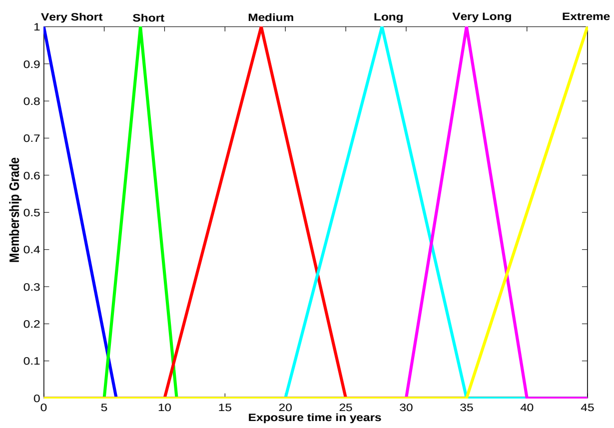



Figure 6.5: Membership functions for exposure time.

**Step 3: Formation of linguistic rule base**

The relationship between input and output are represented in the form of IF-THEN rules. In the proposed model (Fig. 6.2), the $1^{st}$ input (noise level) is taken as X, the $2^{nd}$ input (frequency) is taken as Y, the $3^{rd}$ input (exposure time) is taken as Z where as the output (hearing loss) is taken as T as per the TSK fuzzy system. The inputs X, Y, and Z have been classified to six categories each. Hence, 216 rules have been made in this inference system; the rules are generated in the following ways:

$R^1$: **IF** X is '$X^{(1)}$' **AND** Y is '$Y^{(1)}$' **AND** Z is '$Z^{(1)}$' **THEN** hearing loss (T) is $T=a_1.X+b_1Y+c_1.Z+d_1$;

$R^2$: **IF** X is '$X^{(4.19)}$' **AND** Y is '$Y^{(1)}$' **AND** Z is '$Z^{(1)}$' **THEN** hearing loss (T) is $T=a_2.X+b_2Y+c_2.Z+d_2$; **. .**

$R^{216}$: **IF** X is '$X^{(6)}$' **AND** Y is '$Y^{(6)}$' **AND** Z is '$Z^{(6)}$' **THEN** hearing loss (T) is $T=a_{216}.X+b_{216}Y+c_{216}.Z+d_{216}$

Here, $X^{(1)}_{,}$ $X^{(2)}$ ... $X^{(6)}$, $Y^{(1)}$... $Y^{(6)}$, $Z^{(1)}$.... $Z^{(6)}$ are shown as the linguistic parameters of the inputs (Table 6.1), where as $a_1$, $a_2$,...$a_{216}$, $b_1$,$b_2$....$b_{216}$,$c_1$,$c_2$...$c_{216}$ are shown as the coefficients or tune parameters and $d_1.d_2$.....$d_{216}$ are the bias associated with the output. The output is mostly expressed by these tune parameters and biases, which can be expressed in the following ways (expression-6.1):

$$T = \begin{bmatrix} a_1 & b_1 & c_1 & d_1 & \rightarrow R_1 \\ a_2 & b_2 & c_2 & d_2 & \rightarrow R_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{216} & b_{216} & c_{216} & d_{216} & \rightarrow R_{216} \end{bmatrix} \tag{6.1}$$

**Step 4: Defuzzification**

Centriod of area (COA) method of defuzzification is used for determining the output as discussed in Section 4.2.4, Chapter 4.

**Step 5: Parameter optimization**

After the defuzzification, the model gives the output and the error is minimizing by the proper selection of coefficients. The coefficients are set by trial and error basis, when the predictive value matches the desired value with in error limits, and then the coefficients are fixed. This treatment is quite different from other mathematical or statistical models.

### 6.2.2 Simulation Results

In the proposed model, the simulation environment was built up with MATLAB using Takagi-Sugeno-Kang inference techniques. The detailed flow chart of the proposed model is outlined in the Figure.6.6. In the first step the inputs viz. noise level (X), frequency (Y) and exposure time (Z) are fuzzified using triangular membership function. The rule base has a significant role to design the system. After the formulation of rule-base, the coefficients ($a_i$, $b_i$, $c_i$, $d_{i:}$ $1 \leq i \leq 216$) are suitably selected. These coefficients are multiplied with the inputs in the sequence to generate output as given in Figure 6.6. Finally, the Center of Area (COA) method was used for getting the output. This process is repeated until the prediction results are within the acceptable error limit.

Table 6.2: Comparison between the findings of NIOSH and model prediction for noise levels at 90dB at different exposure and frequencies [32]

| Sl.No. | Exposure time (years) | Hearing loss (dB) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Finding of NIOSH at | | | | | | Model results at | | | | | |
| | | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz |
| 1 | Very short (0-6 years) | -10 | -6 | -5 | -6 | -8 | -6 | -6 | -21 | -5 | -6 | -8 | -8 |
| 2 | Short (5-11 years) | -16 | -12 | -10 | -15 | -25 | -15 | -7 | -22 | -10 | -15 | -25 | -17 |
| 3 | Medium (10-25years) | -16 | -12 | -14 | -30 | -35 | -30 | -7 | -22 | -14 | -30 | -35 | -32 |
| 4 | Long (20-35years) | -20 | -15 | -14 | -30 | -40 | -45 | -10 | -25 | -14 | -30 | -40 | -47 |
| 5 | Very long (30-40years) | -20 | -18 | -25 | -50 | -50 | -55 | -10 | -25 | -25 | -50 | -50 | -57 |
| 6 | Extreme (35-45 years) | -25 | -22 | -35 | -60 | -65 | -60 | -13 | -28 | -35 | -60 | -65 | -62 |

In the model, hearing loss is considered to be a function of noise level, frequency, and exposure time (years). The model has been implemented using Sugeno inference technique, which is able to predict the hearing loss with 5 % error limit. Simulation results are summarized in contour plots and depicted in Figure 6.7. It shows the contour plot of hearing loss as a function of noise level and frequencies at different years of exposure. The counter plots have been plotted at -25 dB, -40 dB, -55 dB and -70 dB hearing loss. As per AAOO criteria, hearing loss up to -40 dB has less significant effect. Above -40dB hearing loss, the hearing losses starts to increase and beyond -70dB it will be significant and hence, comes under the danger zone. As per Figure 6.7, the hearing losses are "not significant (0 to -25 dB)"with increment of noise level (80-115 dB) at "very low (500-1500 Hz)" and "low (1000-3000 Hz)" frequency at 10 years of exposure. When

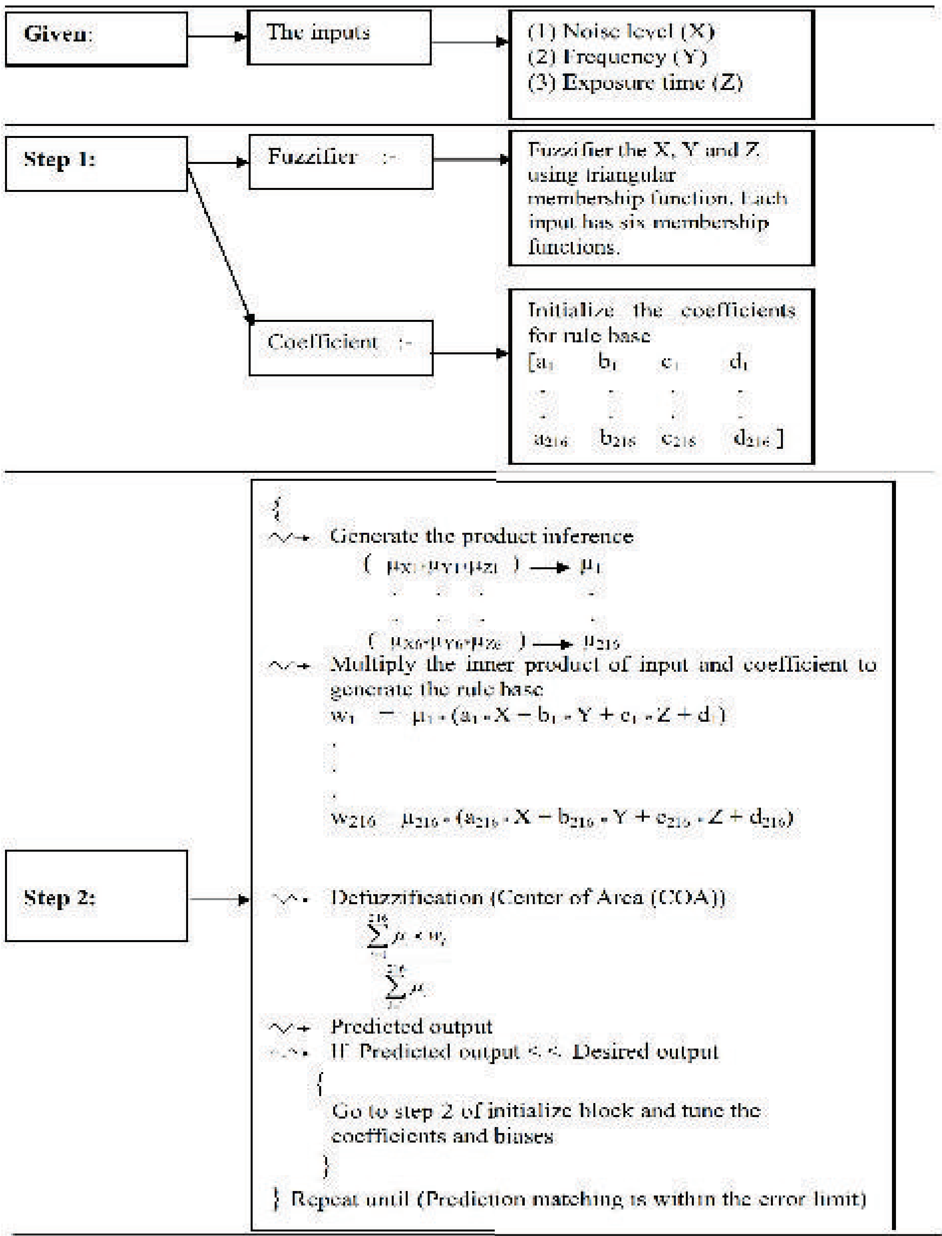



Figure 6.6: Flow chart of the TSK fuzzy based noise induced hearing model.

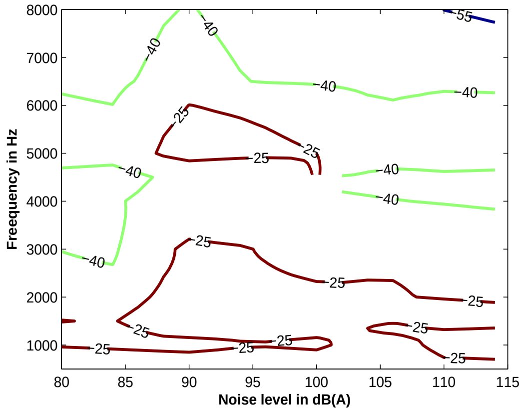
Table 6.3: Comparison between the findings of EPA and model prediction for noise at 85 dB at different exposure and frequencies [34] & [128]

| Sl.No. | Exposure time (years) | Hearing loss (dB) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Finding of EPA at | | | | | | | Model results at | | | | | | |
| | | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 8 kHz | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 8 kHz |
| 1 | Very short (0-6years) | -4 | -6 | -15 | -22 | -23 | -16 | -21 | -4 | -20 | -13 | -20 | -21 | -17 | -23 |
| 2 | Short (5-11years) | -10 | -10 | -28 | -34 | -36 | -32 | -40 | -5 | -20 | -26 | -34 | -34 | -33 | -42 |
| 3 | Medium (10-25years) | -10 | -14 | -30 | -39 | -46 | -42 | -44 | -5 | -20 | -28 | -37 | -44 | -43 | -46 |
| 4 | Long (20-35 years) | -13 | -14 | -37 | -48 | -52 | -50 | -52 | -8 | -23 | -35 | -46 | -50 | -51 | -54 |
| 5 | Very long (30-40 years) | -16 | -20 | -40 | -50 | -60 | -52 | -60 | -8 | -23 | -38 | -48 | -58 | -53 | -62 |

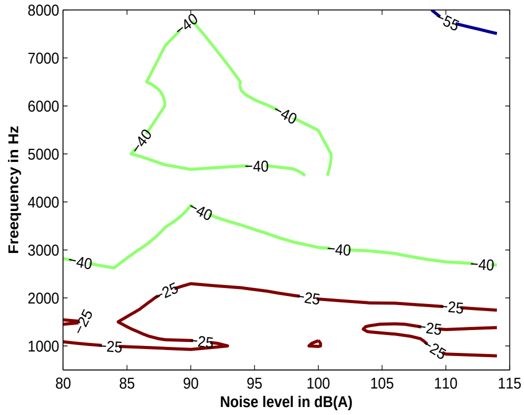
frequency levels is “Extremely high (6000-8000 Hz)”, hearing loss is found “Slight (-20 to -40 dB)” at the same year of exposure. Hearing loss is “not significant” at “very low” frequency but “slight” at “low” frequency range with increase of noise level for medium year (20 years) of exposure. At long year of exposure (30 years), hearing loss is “not significant” at “very low” frequency , “slight” at “low” frequency and found “marked (-50 to -70 dB) at “very high (4500-6500 Hz)” & “extremely high” frequency with increase of the noise level. When year of exposure is more, for example, at “extreme” exposure time (40 years), hearing loss is “not significant” and “slight” at “very low” frequency but found “marked” at “low” frequency. Hearing loss is found “severe (-65 to -85 dB)” at frequency range “4000-8000 Hz” at the noise level of “95-115 dB” for 40 years of exposure.

To check the validation of the model, the model output compared with the survey results of NIOSH and EPA. The survey finding from NIOSH contains different industrial data including mining and the survey finding from EPA is from mining industry. The comparison was at 90 dBA for NIOSH study. A comparison of the model results with NIOSH is shown in Table 6.2. The comparison table shows that at ‘medium’ noise level and at ‘very low’ (500-1000 Hz) frequency, hearing loss is ‘not significant’ (0-25 dB) at different exposure time. At ‘High’ (1000-3000 Hz) frequency, hearing loss belongs to both ‘not significant’ & ‘slight’ (-20 to -40 dB) range at different exposure time. Further, it is found that with the increase of frequency range, hearing loss also increases and can reach up to ‘severe’ (-65 to -85 dB) range with ‘medium’ noise level . It is observed that, at 4000 Hz frequency (‘high’), hearing loss is the highest, which satisfies the audiometric study criteria. The results of NIOSH study closely matches with the model results up to 6000 Hz. It was observed that for 0-6 years of exposure, the hearing loss as per NIOSH was between 0 -20 dB, where as it was between 0 -25 dB (not significant) as per AAOO.

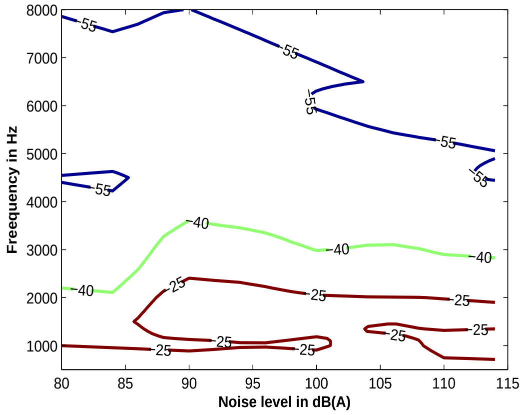
A comparison of the model results with EPA is shown in Table 6.3. The results of EPA study closely matches with model results. The comparison study is at lower noise level



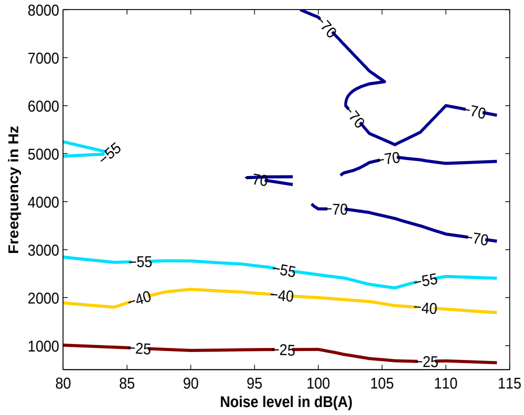

(a) 10 years




(b) 20 years




(c) 30 years




(d) 40 years

Figure 6.7: Hearing loss as a function of frequency and noise level for different years of exposure

(85 dBA) than for the NIOSH study. The EPA comparison study is at 85 dBA exposure level and the study closely matches with the model results up to 8000 Hz. The EPA model does not include extreme exposure time for the workers. However, the fuzzy model takes this account in prediction and gives constant output for the 'extreme' condition.

### 6.2.3 Mamdani Fuzzy Model for Noise Induced Hearing loss Prediction

#### 6.2.3.1 Methodology

In this model, the Noise-induced hearing loss (Y) is expressed as a function of noise level ($X_1$), frequency ($X_2$) and exposure time (years) ($X_3$) can be mathematically expressed as given by eqn (6.2):

$$Y = f(X_1, X_2, X_3) \tag{6.2}$$

Taking in to account all these variables, the function '$f$' becomes very complex and general physical model cannot be constructed. So the choice of input has to be restricted to above three variables. In fuzzy modelling, the function '$f$' is replaced by the relation R that describes fuzzy rules. The model development process comprises of the following steps:

**Step 1: Identification of input and output variables**

The fuzzy system has three input variables: noise level, frequency and exposure time. The output variable is the hearing loss. Figure 6.8, represents Block diagram of Mamdani's MISO (Multi input single output) model. The antecedent is typically a conjugative combination of fuzzy proposition using the individual input variables, (Here 3 inputs) where as the consequent part in a Mamdani's MISO model is usually a single fuzzy proposition.

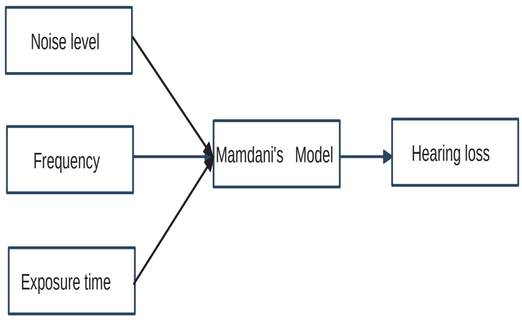



Figure 6.8: Block diagram of Mamdani's MISO model.

**Step 2: Selection of input and output variables:** The inputs and output with their linguistic values and fuzzy intervals are shown in Table 6.1.

**Step 3: Determining the linguistic labels and membership function for various input and output variables**

The inputs variables have been divided in to the following set of terms i.e. noise level ={low, medium, high, very high, extreme, extremely high}, frequency={very low, low, medium, high, very high, extremely high} and exposure time= {very short, short, medium, long, very long, extreme}. The triangular functions were selected due to their simple formula and computational efficiency [168] as shown in Figures. 6.3 to 6.5. The hearing loss output variable has been similarly divided in to hearing loss= {not significant, slight, mild, marked, severe, extreme} using triangular function as shown in Figure 6.9.

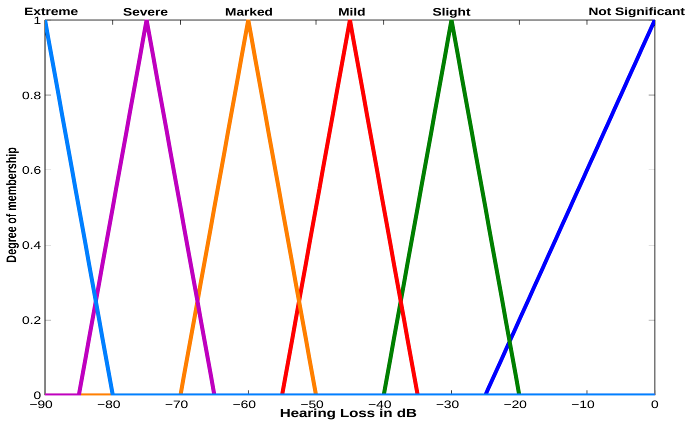



Figure 6.9: Membership functions for hearing loss.

**Step 4: Formation of IF-THEN rules**

The relationship between input and output are represented in the form of IF-THEN rules. As per given inputs and output, a maximum of 216 rules were generated. Out of which, three rules have been illustrated graphically as given in Figures 6.10, 6.11 and 6.12 respectively. The IF-THEN rules are generally represented in the following manner:

Rule 1: IF noise level is low, AND frequency is very low AND exposure time is very short THEN hearing loss is not significant.

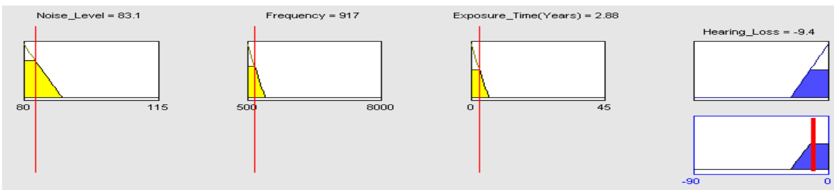



Figure 6.10: The graphical representation of rule 1

Rule 2: IF noise level is medium AND frequency is high AND exposure time is long THEN hearing loss is mild.

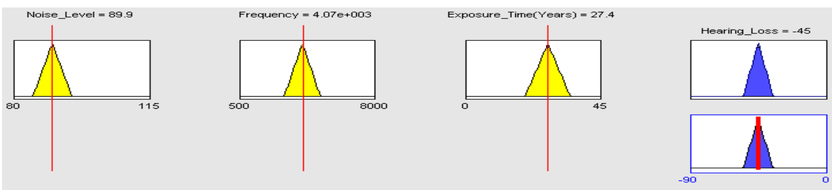



Figure 6.11: The graphical representation of rule 2

Rule 3: IF noise level is very high AND frequency is very high AND exposure time is very long, THEN hearing loss is marked.

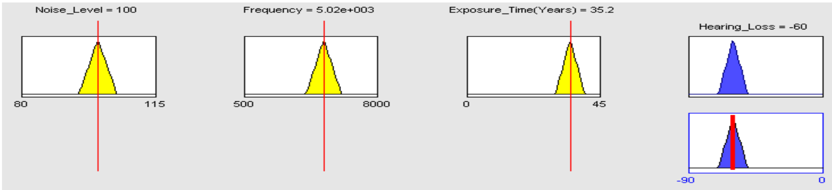



Figure 6.12: The graphical representation of rule 3

**Step 5: Defuzzification**

Centriod of area (COA) method of defuzzification is used for determining the output.

### 6.2.4 Result and discussion

Hearing loss in the present model is considered to be a function of equipment noise level, frequency and exposure time (years). The model has been implemented on fuzzy logic toolbox of MATLAB [212] using Mamdani inference techniques. Figure 6.13, shows plotting of hearing loss versus frequencies at different noise exposure levels based on NIOSH data. It is clear that the hearing loss is 'not significant' (0 to-25dB) for 'very short', 'short', 'medium', 'long', and 'very long' exposure times while it is 'slight' for 'extreme' exposure time at 'very-low' (500-1000Hz) frequency. At 'low' (1000-3000Hz) frequency hearing loss is similar to 'very-low' frequency. When frequency is 'medium' (2000-4000Hz) hearing loss is 'not significant' for 'very short' and 'short' exposure times, slight for medium and long exposure times and 'mild' (-35 to -55dB) for 'very long' and 'extreme' exposure times. At 'high' frequency (3000-5000Hz) hearing loss is 'not significant' for 'very short' exposure time, 'slight' for 'short' exposure time, 'mild' for 'medium' and 'long' exposure time, 'marked' (-50 to -70dB) for 'very long' exposure time and 'severe' (-65 to -85dB) for 'extreme' exposure time. When frequency is 'very high' (4500-6500Hz), it is 'not significant' for 'very short' and 'short' exposure times, 'slight' for 'medium' exposure time, 'mild' for 'long' exposure time and 'marked' for 'very long' and 'extreme' exposure times.

A comparison of the model results with NIOSH is shown in Table 6.4. The results of NIOSH study closely matches with the model results up to 6000Hz. It was observed that for 0 to 6 years of exposure, the hearing loss as per NIOSH was between 0 to -15 dB, where as it was between 0 to -25 dB (not significant) as per AAOO. The model gives a constant value for very short exposure time.

Figure 6.14 shows plotting of hearing loss versus frequencies at different noise exposure levels based on EPA data. It is found from the figure that hearing loss is 'not significant' for 'very short' and 'short' exposure times while it is 'slight' for 'medium', 'long', 'very long', and 'extreme' exposure times at 'very low' frequency. At 'low' frequency, it is 'not significant' for 'very short' exposure time, 'slight' for 'short' and 'medium' exposure times, 'mild' for 'long' and 'very long' exposure times. When frequency is 'medium', hearing loss is 'slight' for 'very short' and 'short' exposure times, 'slight' and 'mild' for 'medium' , 'long' and 'very long' exposure times. Hearing loss is 'slight' for 'very short' and 'short' exposure time, 'mild' for 'medium' and 'long' exposure time and 'marked' for 'very long exposure' time when frequency is 'very high'. When frequency is 'high', hearing loss is 'slight' for 'very short' exposure time, 'mild' for 'short' and 'medium' exposure time and 'marked' for 'long' and 'very long' exposure time. But when frequency is 'extremely high' (6000-8000 Hz) hearing loss is 'slight' for 'very short' and 'short' exposure times, 'mild' for 'medium' exposure time, 'marked' for 'long' and 'very long' exposure times.

A comparison of the model results with EPA is shown in Table 6.5. The results of EPA study closely matches with model results. The EPA model does not include extreme exposure time for the workers. However, the fuzzy model takes this into account in prediction and gives constant output for the 'extreme' condition.

Table 6.4: Comparison between the findings of NIOSHand model prediction for noise levels at 90 dB at different exposure and frequencies [32]

| Sl.No. | Exposure time (years) | Hearing loss (dB) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Finding of NIOSH at | | | | | | Model results at | | | | | |
| | | 500Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz |
| 1 | Very short | -10 | -6 | -5 | -6 | -8 | -6 | -10 | -10 | -10 | -10 | -10 | -10 |
| 2 | Short | -16 | -12 | -10 | -15 | -25 | -15 | -8 | -9 | -8 | -10 | -30 | -10 |
| 3 | Medium | -16 | -12 | -14 | -30 | -35 | -30 | -8 | -9 | -8 | -30 | -45 | -30 |
| 4 | Long | -20 | -15 | -14 | -30 | -40 | -45 | -30 | -30 | -10 | -30 | -45 | -45 |
| 5 | Very long | -20 | -18 | -25 | -50 | -50 | -55 | -30 | -30 | -30 | -60 | -60 | -60 |
| 6 | Extreme | -25 | -22 | -35 | -60 | -65 | -60 | -30 | -30 | -45 | -60 | -75 | -60 |

Table 6.5: Comparison between the findings of EPA and model prediction for noise at 85 dB at different exposure and frequencies [34] & [128]

| Sl.No. | Exposure time (years) | Hearing loss (dB) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Finding of EPA at | | | | | | | Model results at | | | | | | |
| | | 500 Hz | 1kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 8 kHz | 500 Hz | 1 kHz | 2 kHz | 3 kHz | 4 kHz | 6 kHz | 8 kHz |
| 1 | Very short | -4 | -6 | -15 | -22 | -23 | -16 | -21 | -10 | -10 | -11 | -30 | -30 | -10 | -30 |
| 2 | Short | -10 | -10 | -28 | -34 | -36 | -32 | -40 | -10 | -10 | -30 | -30 | -45 | -30 | -45 |
| 3 | Medium | -10 | -14 | -30 | -39 | -46 | -42 | -44 | -10 | -10 | -30 | -45 | -45 | -45 | -45 |
| 4 | Long | -13 | -14 | -37 | -48 | -52 | -50 | -52 | -10 | -10 | -45 | -45 | -60 | -45 | -45 |
| 5 | Very long | -16 | -20 | -40 | -50 | -60 | -52 | -60 | -10 | -30 | -45 | -45 | -60 | -60 | -60 |

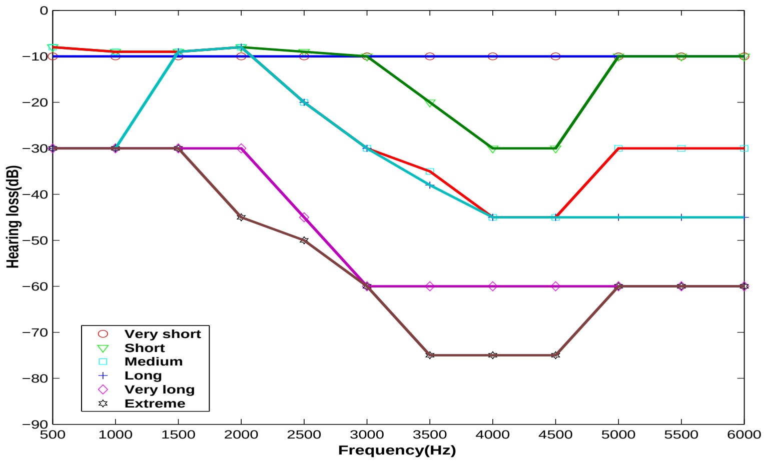



Figure 6.13: Hearing loss as a function of frequency for various exposure times at medium noise level (NIOSH)

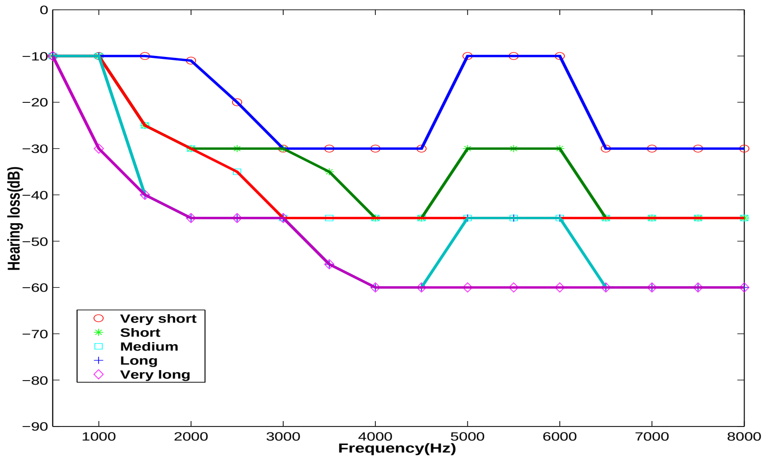



Figure 6.14: Hearing loss as a function of frequency for various exposure times at low noise level (EPA)

## 6.3 Conclusion

The Takagi-Sugeno-Kang (TSK) fuzzy model has been developed based on field surveys of EPA and NIOSH. The model clearly brings out the salient features of the surveys concerning the variation of hearing loss with frequency for various duration of exposure times, viz.; the hearing loss is not appreciable below 2 kHz. The model results closely match with the NIOSH results in 2-6 kHz at 90 dBA and with the EPA results in 2-8 kHz at 85 dBA. It was observed that for 0-6 years of exposure, the hearing loss as per NIOSH was between 0 -20 dB, where as it was between 0 -25 dB (not significant) as per AAOO.

The Mamdani fuzzy model has been developed on the basis of field surveys of EPA and NIOSH. From the model output,it was found that the hearing loss is not appreciable below 2kHz and becomes pronounced between 2-4kHz in case of NIOSH and 3-5 kHz in case of EPA respectively. The model clearly reveals that the duration of exposure can be used to infer the hearing loss for industrial workers of different age groups. From the simulation results, it is observed that T-S-K fuzzy model gives better prediction result compared to Mamdani fuzzy system. It is hoped that the developed models will be quite useful in prediction of NIHL of miners.

# CHAPTER 7

# CONCLUSION

In the thesis noise survey was conducted in two different mines and the frequency and non frequency noise prediction models were developed to predict noise for opencast mining machineries.After using the mathematical models, different soft-computing techniques were used to develop suitable noise prediction models in opencast mines. From the present investigations the following conclusions can be drawn:

- Different soft computing techniques viz. Fuzzy Inference Systems, Multi-layer Perceptron (MLP), Radial Basis Function Network (RBFN) and Adaptive Network based Fuzzy Inference System (ANFIS) were applied for development of non-frequency noise prediction model using VDI-2714. From the simulation result, it was observed that ANFIS gave better noise prediction results as compared to other soft-computing techniques, as it takes very less CPU time (0.0625 sec.) and can be easily implemented in hardware. However, it could be noticed that the other techniques like Fuzzy Logic System, MLP, and RBFN can also be applicable for non-frequency based noise prediction models.

- Soft-computing techniques viz. Fuzzy Inference Systems, MLP, RBFN and ANFIS were successfully applied for development of frequency dependent models. Soft-computing models were applied to CONCAWE, ISO-9613, ENM etc. From the comparison of all soft-computing models, Radial Basis Function Network and ANFIS results match closely with the mathematical models with minimum Root Mean Square Error (RMSE).

- Comparing the different techniques of soft computing models for both frequency and non-frequency based noise situation, it was found that ANFIS gives very close and better noise prediction results compared to both frequency and non-frequency based noise prediction models with less RMSE.

- Anderson-Darling (AD) normality test was carried out for all the soft computing models. From the results, it was found that the p-value of the normality plots was found above 0.05 for all the models. It signifies that the residue follows normal distribution. Small percentage of error proved the suitability of the above models for practical engineering applications.

- For prediction of Noise induced hearing loss (NIHL), fuzzy logic techniques like Mamdani Fuzzy logic system and T-S-K fuzzy logic systems were used. No mathematical models are available for predicting NIHL of industrial workers as yet.Among the fuzzy techniques and from the simulation results, it was observed that the T-S-K fuzzy logic system gives better prediction of NIHL vis-à-vis Mamdani fuzzy system.

- Audiometry studies are carried out to assess the threshold of hearing of workers. This helps in understanding the level of hearing loss of each ear at different frequency levels. By knowing the results of the studies, it is possible to undertake hearing conservation programs by providing hearing protection devices and limiting workers exposure to high levels of machinery noise.

- Noise contours were plotted for an opencast mine and it can be useful for noise zoning and mapping to minimize workers exposure as per statutory prescribed limits.

## 7.1 Contribution in the thesis

Contribution of the thesis can be listed as under

- Predict noise in mining environments, is very complex task. Use of statistical models, mathematical models such as CONCAWE, ISO-9613-2, VDI-2720, ENM etc. are complex. Soft-Computing based model is very easy to use, in simple word, it is very user friendly.

- With high uncertainty conditions, any statistical model cannot give appropriate result, Soft-Computing based models, which are designed on a learning algorithm, can predict good result at any complex situation or uncertainty condition.

- Cost of the software for predicting noise as per CONCAWE , ISO-9613-2 and ENM model are high, hence it is not possible for small scale mines to use. Developed model designed for both frequency or non-frequency based noise prediction model. Hence, it will benefit for both small scale and big scale mines to predict noise according to their need.

- The developed soft computing based noise prediction model can predict noise with any new set of input condition. It means, in any new mining environment condition, there is no need to change the structure of the model, it can perform well with new input set, where mathematical model do not perform well with new set of data.
- The developed model can be implemented in hardware.
- Once the mathematical model or statistical model developed, the model has fixed with boundary value of the input parameters and never predict beyond the range of the input parameters. Where as soft computing based model can predict beyond the range of the input parameters, in mathematical word, it has good extrapolation capability.
- For a particular mine, it was not possible earlier to predict noise as per various standard or models. However, in this study all types of frequency dependent models, CONCAWE, ENM, ISO-9613-2, NORDFORSK and VDI-2720 were applied with soft computing techniques. Hence multiple options are available at any mine to use according to their need.
- Fuzzy Logic System (Mamdani and Sugeno) based hearing loss model developed work well with small training data set. Using this model, any industry can predict noise induced hearing loss of their employees without any real time data or medical checkup.

## 7.2 Future Scope

- The entire soft computing model can be developed by using GUI application.
- For updating the model error, Least Mean Square method was applied. The error can be minimized by applying evolutionary algorithms.
- Complex hybrid architecture like Fuzzy-ANN-GA, Fuzzy-Rough-GA can be implemented in future to develop advanced soft-computing model.
- Hardware implementation of the proposed methods can be taken up.
- Health risk assessment of mining workers using audiometry and dosimetry can be carried out.

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# RESEARCH PUBLICATIONS

## International Journals

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