INVESTIGATIONS ON PERFORMANCE OF LOAD HAUL DUMPERS IN UNDERGROUND MINES AND IMPROVEMENT OF ITS AVAILABILITY AND UTILIZATION USING RELIABILITY ANALYSIS

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

By

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February, 2021

DECLARATION

by the Ph.D. Research Scholar

I hereby *declare* that the Research Thesis entitled **"Investigations on Performance of Load Haul Dumpers in Underground Mines and Improvement of its Availability and Utilization using Reliability Analysis"** which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy in **Mining Engineering** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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This Thesis is dedicated

to

my family members & my son

Master. ***Joel Rhian Jakkula***

CERTIFICATE

This is to certify that the Research Thesis entitled“**Investigations on Performance of Load Haul Dumpers in Underground Mines and Improvement of its Availability and Utilization using Reliability Analysis**” submitted by **Mr. Balaraju Jakkula** (**Register Number:** 158003 MN15F06) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of Doctor of Philosophy.

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ABSTRACT

Every organization in today's competitive world intends to improve its economy by increasing their production and productivity rates. Unequivocally, the production in Indian underground mines over the years is not satisfactory, due to a variety of reasons. There are manifold of avenues for the betterment of production and one such approach is through enhanced utilization of mechanized equipment such as Load Haul Dumper (LHD). These LHDs are prone to continuous and random occurrence of numerous potential failures during the operation. Understanding of each failure mode will help to take an appropriate maintenance action, which leads to reduce the downtimes of the machinery. One approach of productivity improvement efforts is through an increase in percentage availability and utilization of these machines. The higher availability and utilization of these machines under certain operating constraints, leads to an increase in the production and productivity of these capital intensive equipment. The accomplishment of this goal can be possible only with the improvement of the reliability of equipment by reducing the occurrence of breakdowns. The purpose of the research performed for this thesis is to make an attempt to control the occurrence of uneven breakdowns, by using reliability analysis. The developed methods can be used to identify the problems/causes affecting LHD downtime, to assess suitable maintenance management strategies for repair and replacement action and to identify the economic lifetime of LHD systems.

The major objective can be explained as providing quantitative forecasts of diverse performance characteristics of LHDs through reliability computations, evaluations, and forecasts. Such characteristics are Reliability, Availability, and Maintainability (RAM), downtimes, frequency of failures, and Overall Equipment Effectiveness (OEE) of the system. The estimation of these characteristics is significant for optimal decision making. To perform the reliability analysis, a fleet of LHDs deployed at both coal and non-coal mines of M/s The Singareni Coal Collieries Company Limited (SCCL), Telangana, M/s The Hutti Gold Mines Company Limited (HGML), Karnataka, and M/s The Hindustan Zinc Limited (HZL), Rajasthan were selected to carry out the field investigation for collection of failure and repair data of equipment.

Before performing the reliability analysis it is necessary to perform the trend and serial correlation tests to determine whether and how the failure patterns are changing with respect to time and to validate the Independent and Identical Distribution (IID) nature of the data sets. As the data have been collected from the field investigations and if such tests are not performed, then there is a possibility of arriving at incorrect conclusions. On analysis it has been found that the time between successive failures (TBFs) of LHDs is free from the presence of trends. Statistical based analysis like statistic U-test (Chi-squared test) has been carried out to determine the method for reliability modeling. Generally, the Renewal Process (RP) method can be utilized for perfect repairs and the Non-Homogeneous Poisson Process (NHPP) method can be utilized for minimal repairs. However, most repair activities may realistically not result in such two extreme situations but are a unique combination in this range. In this study, the RP approach has been utilized to perform the reliability analysis for estimation of percentage of each sub-system (i.e., Engine, Braking, Transmission, Tyre, Hydraulic, Electrical and Mechanical) reliability and failure rate of the LHDs.

Best-fit distribution of data sets have been identified by the utilization of Kolmogorov-Smirnov (K-S) test. Maximum Likelihood Estimate (MLE) method has been used to estimate the theoretical probability distribution parameters (η, β, and γ) of best-fit curves. Reliability of each individual sub-system has been computed according to the best fit distribution. In addition to the operational procedures and technical expertise, maintenance efficiency is also a significant factor that needs to be considered for assessment of system performance or effectiveness. Improvement of performance of the equipment mainly depends upon the adoption of suitable maintenance management actions (repair/replacement). Keeping this in view, in this analysis maintainability percentages has been estimated for the LHDs after successful identification of best-fit probability distribution function. Further, the reliability-based Preventive Maintenance (PM) time intervals were forecasted for the enhancement of equipment reliability.

In this research work, the most appropriate methods of reliability modeling and optimization such as Failure Mode Effect Analysis (FMEA), Reliability Block Diagram (RBD) and Fault Tree Analysis (FTA) are presented to estimate the percentage of reliability, availability, and maintainability (RAM). The FMEA approach has been utilized in this research study to investigate the failure behavior of the LHDs. FMEA identifies the reasons for occurrence of potential failure modes and provides the necessary recommendations or corrective actions to reduce the uneven occurrence of failures. The risk-based numerical assessment was made with prioritization of critical failure modes through the Risk Priority Number (RPN) calculation. A new risk management approach known as "MATLAB Fuzzy rule based interface system" was utilized to validate the calculated RPN values. The series and the parallel configuration systems are the two important approaches in RBD approach and are widely used to estimate the overall system reliability of the LHDs. In this study, all the connections of the components in a machine have been identified in series configuration system. Hence, the overall system reliability of the LHDs were estimated using series configuration system calculation. In addition to that, the reliable life (T_R) of the equipments were also calculated to forecast the duration (threshold time) for occurenance of next subsequent failure. In this study, FTA was carried out to identify the percentage of unavailability of the system and to know the influence of each component/ cut set/ critical part on the system failure. Further, the computed values of reliability, availability and maintainability were validated with MATLAB based Artificial Neural Network (ANN) results for identification of percentage error value. In addition to this, an attempt has been made for the improvement of performance of the equipment through evaluation of Overall Equipment Effectiveness (OEE). The OEE percentage of each LHD has been computed in terms of percentage availability, performance and quality. This thesis provides a scientific base for evaluating the reasons for performance drop of the equipment and suggests the necessary remedial measures and recommendations to the mining industry for the improvement of performance on the basis of RAM analysis and OEE calculations.

Keywords: LHD; Breakdown; Reliability; Availability; Maintainability and OEE.

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LIST OF ABBREVIATIONS

GDP	Gross Domestic Product
CAGR	Compound Annual Growth Rate
CSO	Central Statistic Office
WCA	World Coal Association
WCI	World Coal Institute
CIL	The Coal India Limited
SCCL	The Sinagareni Coal Colleries Company Limited
HZL	The Hindustan Zinc Limited
Mine-A	Sindesar Khurd Mine
Mine-B	Mallapa Shaft Mine
Mine-C	Godavarikhani (GDK)-11 Mine
Mt	Million Tonnes Bt

Billion Tonnes LHD

Load Haul Dumper

OEE	Overall Equipment Effectiveness
OEP	Overall Equipment Performance
RAM	Reliability, Availability and Maintainability
KPIs	Key Performance Indicators
RBD	Reliability Block Diagram
FTA	Fault Tree Analysis
FMEA	Failure Mode and Effect Analysis
ANN	Artificial Neural Network
FIS	Fuzzy Interface System
RP	Renewal Process
HPP	Homogeneous Poisson Process
NHPP	Non- Homogeneous Poisson Process
TBF	Time Between Failure
TTR	Time To Repair
FF	Failure Frequency

CTBF	Cumulative Time Between Failure
CTTR	Cumulative Time To Repair
CFF	Cumulative Failure Frequency
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
MTTF	Mean Time To Failure
PLP	Power Law Process
FR	Failure Rate
PDF	Probability Density Function
CDF	Cumulative Distribution Function
MAMT	Mean Active Maintenance Time
MDT	Mean Down Time
PM	Preventive Maintenance
CM	Corrective Maintenance
As	System Availability
Rs	System Reliability
Ms	System Maintainability
ORs	Overall System Reliability
Ss	Supply Effectiveness
Mw	Maintainability
K-S	Kolomogorov-Smirnov
MLE	Maximum Likelihood Estimation
IID	Independent and Identical Distribution
IEC	The International Electro Technique Committee (IEC)
MKV	Markov Modelling Analysis
RPN	Risk Priority Number
SC	Soft Computing
S	Severity
O	Occurence
D	Detection
TPM	Total Productive Maintenance

LDBH Large Dia Blast Hole

RG Ramagundam

SSH Shift Schedule Hours MAH

Machine Available Hours SMH

Scheduled Maintenance Hours IDH

Idle Hours

SSE Sub-system of Engine

SSBr Sub-system of Brake

SSTy Sub-system of Tyre

SSH Sub-system of Hudraulics

SSEl Sub-system of Electricals

SSTr Sub-system of Transmission

SSM Sub-system of Mechanical

T_R Reliable Time

DOF Degree of Freedom RCA

Root Cause Analysis RMSE Root

Mean Square Error CBM

Critical Breakdown Mode

CFMI Critical Failure Mode Index

C-RPN Conventional Risk Priority Number

F-RPN Fuzzy Risk Priority Number

LCC Life Cycle Cost

LIST OF NOTATIONS

t	Failure Time
η	Scale Parameter
β	Shape parameter
γ	Location Parameter
λ	Failure Rate
C	Constant
ε	Level of Significance
T_n	n^{th} Value of TBF
n	Population Size
y	Output Response

CHAPTER-1

INTRODUCTION

Mining and minerals are the primary resources for the development of worldwide industrial sectors. Among all the industries, mining is ranked as the second basic industry of early civilization after agriculture. Humans began the mining process approximately about 4,50,000 years ago (Hartman, H., and Mutmansky, J. 2002). In pre-historic times, mining has become an essential requirement for the survival of human beings in society. They fulfilled their day to day requirements from the extracted naturally available mineral substances in the earth or other heavenly bodies (Hartman, H.L. 1987). Metals from mined out minerals and related substances such as Stone, Copper, Bronze, Iron, Zinc, and Gold, etc. are essential for society and are being used in the daily life of human beings. India has significant potential to further grow its mining industry. This potential is evident from both the demand for minerals and the availability of natural resources in India. The production and productivity of Indian underground mines from the past few decades is not at satisfactory level, due to less mechanization and variety of operational and policy factors. Mechanization is a powerful tool that enhances the human capacity and allows timeliness, efficiency, and consistency in field operations. The accomplishment of projected targets of production and productivity can only be possible by maintaining and utilizing the equipment in a more efficient and effective manner. Appropriate and timely maintenance can lead to an increase in the available time of the machine for production activities in the work environment. Hence, it is very essential to recognize and asses the present working status of the equipment through a detailed performance evaluation.

Reliability and Maintainability (R&M) are the two important components in the maintenance, operation, design and development of today's complex electro-mechanical systems. Assessment of R & M can provide a sound base for deciding the availability of spare parts, required part/component improvement plans; redesign actions, allocation of assets, and other management measures to assure that the indicated reliability and maintainability requirements will be met. An investigation plan of reliability and maintainability can identify, and classify the various critical failure modes, identify causes/reasons for the occurrence of sudden failures, predict the equipment performance, and suggest suitable coordination measures such as timely repair, and replacement actions for performance improvement. In industries like aviation, nuclear, oil and gas, as well as mining industry applying the concepts of reliability engineering and analysis during the past few decades has led to the improvement of equipment's health and safety. Reliability analysis is an approach used to estimate the performance of any kind of equipment. Equipment performance mainly depends upon the working place ambience, effective utilization of equipment, operational and maintenance credentials and industrial expertise of the machine operators. These performance estimations are helpful to improve organization of the maintenance and operational activities for the achievement of projected production levels (Oyebisi, T. 2000).

1.1 STATUS OF MINING INDUSTRY IN INDIA

Minerals establish the foundation of mining evolution and India has been prominently bestowed with this endowment of nature significantly. The economic growth of any country depends upon the performance of the core Industrial sectors and mining is like a back-bone among them. The number of reporting mines in India excluding atomic, fuel and minor minerals in the year 2017-18 were 1,430 and are located in 21 States. Among them, 638 belong to metallic minerals and 792 are non-metallic minerals (Indian minerals year book, 2018). The mining sector not only does contribute to Gross Domestic Product (GDP) increment, it also acts as a catalyst for the growth of other core Industries such as cement, steel, power which are essential for the overall improvement of the Nation's economy (Ministry of Mines, Annual Report 2017-18).

1.1.1 Role of Mining in Indian Economy

The Mining industry in India is a major economic activity that significantly contributes to the Indian economy. The Gross Domestic Product (GDP) is one of the most extensively used indicators for identifying the status of economic activities. The National Income and Product Accounts (NIPA) are the basis for measuring the GDP value and it allows the policymakers, statisticians, economists and industrialists to investigate the effect of monetary and fiscal policies, taxes and expenditure strategies on economic development. A wide variety of sectors can contribute to growth of the Indian economy, Viz: hospitality and tourism; transportation and communication, etc. The manufacturing sector accounts for 15%; 8% by from construction sector and 5% is from mining, quarrying, electricity, gas and water sectors (Trading Economics, 2020).

The Indian Mining Industry report of FICCI (2018) states that, the Indian mining sector has witnessed negative growth in past few years. The contribution of mining to India's GDP has fallen from 3.4% in 1992-93 to less than 1% (non-fuel, non-atomic) in 2016. The mining sector's contribution to the country's GDP has been declining in recent years, despite growth in production and value accretion. From 1.93% in 2012-13, the mining sector's share of GDP (excluding petroleum & natural gas) fell to 1.53% in 2017-18. India's GDP grew from 5% to 7% during the same period. However, the mining sector's diminishing contribution to GDP seems to belie its vast untapped potential (Mining's share of India's GDP, June 2019, Available at: https://www.business-standard.com). This de-growth is having its repercussions on the economy as a whole. India needs an evolving and growth oriented mineral development and a mining sector that can foster systematic and sustainable growth in the economy. Indian mining industry is characterized by limited mechanization and relatively lower maturity from the perspective of technology adoption, sustainability and business processes. One of the measures of the same is limited scale of mining operations as evident from the number of operating mines (The Indian Mining Industry report, FICCI, 2018)

1.1.2 Status of Underground Coal Mining

Coal has been an essential factor to build the present-day economies for quite a long time. From early mining traditions to present-day ultra-supercritical power generation sectors and production of steel, the narrative of coal is one of an un-interrupted advancement and improvement in technologies and practices. This story keeps on continuing in the 21st Century also. Coal's effect on present-day society and individuals will be constantly improved by building on its positive commitment to building current economies and social orders and decreasing the ecological effect of its production and use. World Coal Association (WCA) demonstrated that every coal mining country strongly believes that building economic value, protecting the environment and supporting their communities are essential to ensure they make a positive commitment to society (Basic Coal Facts, February 2017).

In India, Coal is the main resource for the generation of power and about 75% of the coal is consumed for energy generation (The India energy portal report, 2018). India ranks 3rd among the coal-producing countries of the world. About 80% of coal production is achieved from open cast mines and the rest of the coal is produced from underground mines (Ministry of Coal, 2005). The maximum quantity of coal is utilized for fulfilment of domestic energy requirements, power plants, steel and cement industries. The power sector consumes about 75% of coal for electricity generation and rest of the coal is consumed for steel and cement and other industries (http://www.worldcoal.org, SRI-C; 2018). Due to this continuous demand, the production levels of coal increased from 70 Mt (early 1970s) to 382 Mt (2004-05) (Ministry of Coal, 2005) and to the current level of 660 Mt (2019-20) (Dept. of Industry, Innovation and Science, 2019, https://www.industry.gov.au/oce). The coal industry faces challenges related to issues such as land acquisition delays, multiple authorizations of stakeholders and ineffective utilization of mechanized machinery in the mines leading to decrease of coal production (TERI-Commercial coal mining report, 2018).

According to the Energy and Resources Institute (TERI) 2018 report, the Government's recent effort to construct several 4000 MW power plants under Ultra Mega (UM) power plants would require coal blocks with reserves of 600-700Mt. Hence, the projected coal demand for the year 2024-25 for production of power, steel, cement, and others is about 1147 Mt. Therefore, the present 6% growth in coal production would not be sufficient to fulfill the demands. In India, 80% of the coal production share is from M/s The Coal India Limited (CIL), 15% share is from M/s The Singareni Coal Collieries Company Limited (SCCL), and the remaining share of 5% is from other captive mines (Souvenir SCCL, 2010, https://scclmines.com).

- **Coal reserves in India:**

As a result of exploration carried out up to the maximum depth of 1200m by the Geological Survey of India (GSI), Central Mine Planning and Design Institute (CMPDI), Mineral Exploration Corporation Limited (MECL**),** etc., a cumulative total of 319.02 Bt of Geological resources of Coal have so far been estimated in the country as on April 01,2018. The details of coal reserves in India as per the geological survey of 2017-18 are given in Table 1.1. The progress of coal reserves in the country during the last 5 years (Updated on April 04,2019) is furnished in Table 1.2.

Table 1.1 Details of coal reserves in India (Million tonnes)

State	**Proved**	**Indicated**
Jharkhand	6,150	83,152
Odisha	7,739	79,295
Chhattisgarh	2,202	57,206
West Bengal	4,643	31,667
Madhya Pradesh	3,875	27,987
Telangana	2,651	21,702
Maharashtra	2,048	12,299
Andhra Pradesh	432	1,581
Bihar	392	1,367
Uttar Pradesh	0	1,062
Meghalaya	471	576
Assam	3	525
Nagaland	402	410
Sikkim	43	101
Arunachal Pradesh	19	90
Total	**31,069**	**3,19,020**

(Source: Geological Survey of India, 2017-18)

Table 1.2 Progress of coal reserves in the country (Million tonnes)

Inventory as on	**Proved/ Measured**	**Indicated**	**Inferred**	**Total**
1.4.2018	1,48,787	1,39,164	31,069	3,19,020
1.4.2017	1,43,058	1,39,311	32,780	3,15,149
1.4.2016	1,38,087	1,39,151	31,564	3,08,802
1.4.2015	1,31,614	1,43,241	31,740	3,06,596
1.4.2014	1,25,909	1,42,506	33,149	3,01,564
1.4.2013	1,23,182	1,42,632	33,101	2,98,914

(Source: Geological Survey of India, 2017-18)

Production, Demand, and Supply of Coal in India

As on 31st March 2013, the Nationalized Coal Sector comprised of 10 Public Sector Companies for coal production in India. Among them the Coal India Limited (CIL) and the Singareni Collieries Company Limited (SCCL) are the major stakeholders for contribution of 91.3% of coal production in 2012-13. The Indian coal sector has a robust demand in the recent years and that requires a huge growth rate in coal production. The production of raw coal increased from 556.40 Mt (in 2012-13) to 633.34 Mt (in 2016-17) and the estimated production of coal is 1120Mt for 2021-22 (Table 1.3). The contribution of the public sector and private sector in the production of raw coal are given in Table 1.3, and a bar-chart of the production plan is shown in Figure 1.1. The contribution of CIL in the coal production in 2016-17 was 525.38 Mt (80.72%) and the SCCL was 52.24 Mt (9.67%) respectively. The production has been estimated to reach 700.00 Mt by the CIL and 63.00 Mt by the SCCL (Y-o-Y basis) for 2021-22. From the records of Year-End review, 2018-19: Ministry of Coal, the reported production of raw coal was 433.896 Mt in the year 2018-19 as compared with the previous year production of 394.910 Mt. Hence, the overall growth in coal production for the year 2018 was reported as 9.8%.

Table 1.3 Plans for coal production by the CIL, SCCL and Others in 2021-22

(Million tonnes)

Company	2012-13 (Actual)	2013-14 (Actual)	2014-15 (Actual)	2015-16 Target	2015-16 (Actual)	2016-17 Target	2016-17 (Actual)	2021-22 Projection Plan
ECL	033.91	036.05	040.00	042.13	026.11	045.16	028.24	056.02
BCCL	031.21	032.61	034.51	035.85	025.40	040.90	026.80	045.45
CCL	048.06	050.02	055.65	060.60	041.46	065.70	040.48	079.14
NCL	070.02	068.64	072.48	078.10	056.48	079.25	062.38	090.62
WCL	042.29	039.73	041.15	045.10	030.30	046.10	041.13	065.80
SECL	118.22	124.26	128.28	137.00	096.17	130.00	111.00	150.24
MCL	107.89	110.44	121.38	150.00	097.39	142.00	102.25	160.61
NEC	000.61	000.66	000.78	001.22	000.17	001.82	001.28	002.34
CIL	452.21	462.41	494.23	550.00	373.48	600.00	525.38	700.00
SCCL	053.19	050.47	052.54	056.00	043.24	058.45	052.24	063.00
Others	051.00	052.89	065.67	094.00	030.76	096.00	055.86	339.00
Total	**556.40**	**565.77**	**612.44**	**700.00**	**447.48**	**754.45**	**633.34**	**1102.00**

(Source: Ismenvis, Coal & Lignite 2015-16)

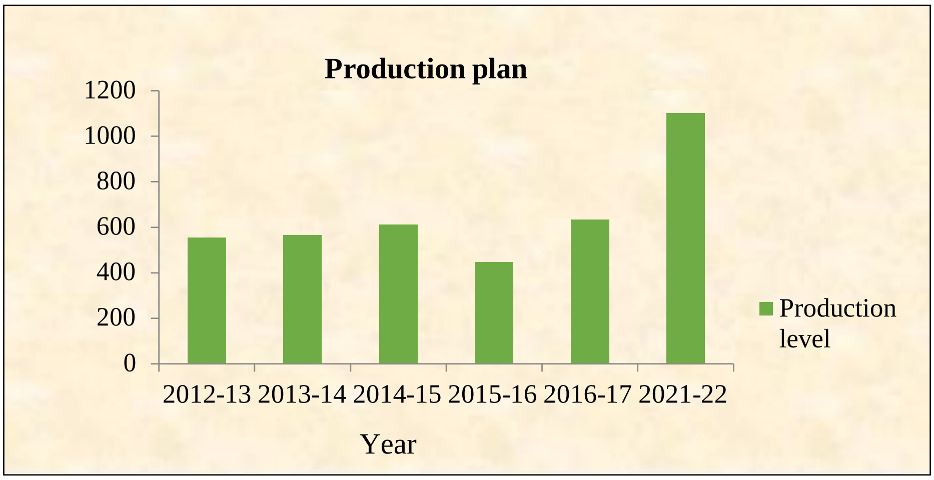
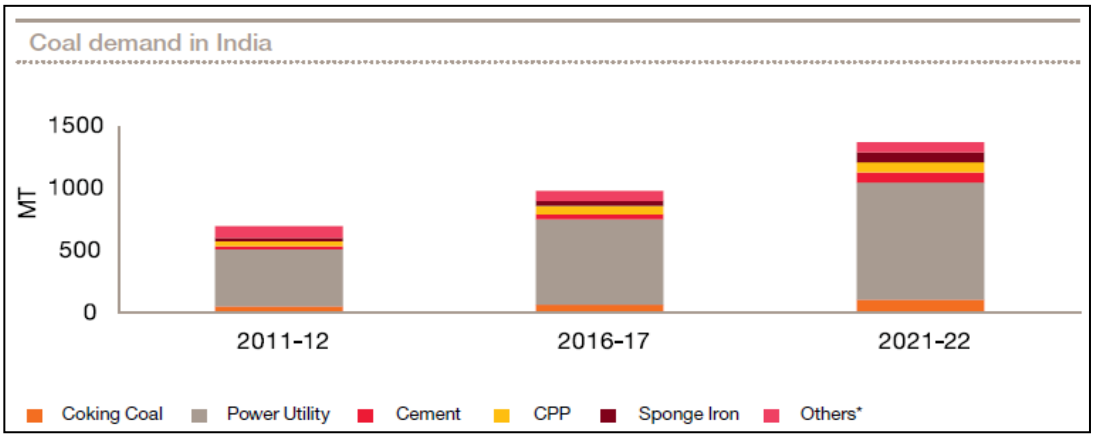


Figure 1.1 Production Plan (Million tonnes)

The overall long-term demand for coal is closely linked to the performance of the end-use sectors. In India, the end-use sectors of coal mainly include electricity, iron and steel, and cement. Depending on their relative prices, the demand for coal, firewood and biomass are relatively less for small scale industries such as bricks and ceramics. Other industries using coal have only a marginal impact on the long-term demand for coal.

The report of the Working Group on Coal and Lignite for the 12th Five Year Plan projects the coal demand in India to grow at a CAGR of 7.1% till 2016-17 and reach 980.5 Mt annually under realistic demand.



*Others in 2011-12 include e-auction quantity.

Figure 1.2 Sector-wise coal demand in India for future

(Source: The report of Working Group on Coal and Lignite for the 12th Five Year Plan, 2016-17)

Coal mining in India has a history of over 235 years. The industry currently occupies a covetable 3rd place in world coal production after China and the USA with a 10% share of total global coal production. India produces about 15% of coal from underground mines. At the time of nationalization (1971) of the coal industry, the contribution of national coal production by opencast and underground mines was 77.45% and 22.55% respectively. The 12th Plan Working Group on Coal and Lignite has assessed a coal demand of 980.50 Mt by terminal year, i.e., 2016-17.

To meet the country's growing demand for coal, foreign collaborations with advanced coal producing countries are also being considered by the Government to bring in new technologies both in underground and opencast sectors for efficient management of the Coal Industry along with building adequate support mechanism through comprehensive skill development and training activities. The Indian government has put thrust on the up-gradation of technology in underground coal mining, for which the Board and Pillar (B&P) method with a higher degree of mechanization will be put in. The mechanization trend in the bord and pillar method of coal mining introduced sophisticated automated side discharge loader (SDL)/ load haul dumper (LHD) machines for loading of coal in place of manual loading. Among the face loading machines, the electric LHD is now the dominant machine in intermediate technology in underground mines and plays an important role in the district or overall mine production. To achieve targeted coal production and to survive the intense competition in the mining industry in recent years, it is imperative that LHD machine as a system and its subsystems should be reliable and maintained effectively and efficiently.

1.1.3 Status of Underground Metal Mining

India holds a fair advantage in the cost of production and conversion costs in both metallic and non-metallic minerals. India produces as many as 95 minerals, which includes 4 fuel, 10 metallic, 23 non-metallic, 3 atomic and 55 minor minerals (including building and other materials). The rise in infrastructure development and automotive production is driving growth in the sector. Power and cement industries are also aiding growth in the metals and mining sector. Demand for iron and steel is set to continue, given the strong growth expectations for the residential and commercial building industry.

The Indian mining industry is portrayed by an enormous number of small operational mines. The number of mineral producing mines (excluding atomic, fuel and minor minerals) in India was reported as 1531 in 2017-18 as against 1508 in the previous year. Out of 1531 reporting mines, 230 were located in Tamil Nadu State, followed by 10 more states such as in Madhya Pradesh-197, Gujarat-191, Karnataka-142, Odisha-132, Andhra Pradesh-129, Chhattisgarh-112, Goa-87, Rajasthan-85, Maharashtra-75 and Jharkhand-58. These States collectively accounted for 94.00% of the number of total mines in India in the year 2017-18. The numbers of reporting mines are given in Table 1.4.

Table 1.4 Number of reporting Mines in 2015-16 and 2016-17
(Source: Ministry of Mines, Annual Report 2017-18)

Sector	**2015-16**	**2016-17 (P)**	**2017-18 (E)**
All Minerals*	1619	1508	1531
Metallic Minerals	715	644	657
Non-Metallic Minerals	904	864	874

*Excluding atomic, fuel and minor minerals.

Based on the production volume, India is in 4th ranking position amongst the mineral producer nations, after China, United States, and Russia, as per the report on Mineral Production by International Organizing Committee for the World Mining Congress, during 1999-2000. However, it was ranked to 8th based on the value of Mineral production, during 2009 (FICCI Mines and Metals Division October 2013 and Ministry of Mines, Annual Report 2017-18). The statistics of Indian and worldwide mineral production details along with its rank/position are given in Table 1.5.

Table 1.5 Contribution and rank of India in Worldwide mineral production

Commodity	**Unit of Commodity**	**Production Quantity**		**Contribution (percentage)**	**Worldwide India's rank**
		World	**India***		
Metallic Minerals					
Bauxite	'000 tonnes	289000	24664	8.53	5th
Chromite	'000 tonnes	34800	3727	10.71	4th
Iron ore	Million tonnes	3305	192	5.81	4th
Manganese ore	'000 tonnes	51200	2393	4.67	6th
Industrial Minerals					
Magnesite	'000 tonnes	29800	299	1.00	10th
Apatite & Rock phosphate	'000 tonnes	276000	1181	0.43	17th
Metals					
Aluminum	'000 tonnes	58800	2896	4.92	4th
Copper (refined)	'000 tonnes	23400	787	3.36	6th
Steel (crude/liquid)	Million tonnes	1623	97.44	6.00	3rd
Lead (metal)	'000 tonnes	11300	142	1.25	14th
Zinc (slab)	'000 tonnes	13800	672	4.87	4th

(Source: World Mineral Production, 2012-2016; British Geological Survey).

* Statistics communicate to 2016-17.

Note: Data inspect of World Mineral Production is on the calendar year basis; however, the data on India's production is based on the financial year.

To reach the future targets of mineral production demand, the Government of India is planning to establish greater coordination among the Central and State, mineral industry, academic and research institutions.

1.2 RATIONALE OF THE STUDY

At the end of the financial year 2018, the growth rate in the production of the mining industry across India was about 2.3% (Statista Resource Department, 2019). Mining production in India is expected to grow at 2.9% by the end of this quarter (2020), according to Trading Economics global macro models and analyst's expectations. Looking forward, the estimation of mining production in India too stands at 2.10% in the year 2021-22 (Trading Economics, 2020). It is very essential to reach the expected targets of production and productivity to remain competitive in today’s globalised world. The accomplishment of this can be possible only by maintaining the mining equipment’s availability, and reliability at the maximum possible levels. Unfortunately, this is not the case, due to the occurrence of a wide variety of un-even and frequent failures. Even though this is the reality, these could be minimized through the adoption of better managerial practices, timely inspection, proper guidance and motivation to the operators of the equipment.

In India, both large and small scale mines utilize a diversified range of mobile mining equipment for the extraction of metallic and non-metallic minerals. The operation of unreliable equipment can have catastrophic consequences for health and safety. These consequences are results of critical equipment breakdowns and system failures. The uneven occurrence of a wide variety of breakdowns and its related downtime considerably contributes to the annual operational, maintenance and production costs of the mine. The reduction of these failures can be possible by maintaining the equipment in fully functioning mode. Therefore, to enhance the anticipated reliability it is very essential to carry out the analysis for the failure data using graphical, analytical and statistical techniques (Nick. Vagenas and Tony. Nuziale. 2001).

1.3 ORIGIN OF THE RESEARCH WORK

In the present scenario of intense global competition, many varieties of mining machinery are being utilized to enhance the production and productivity, to reach the expected targets of production in underground mines. An observation of the historical records of Indian underground mines showed that the record of production and productivity over the years is not encouraging, perhaps, due to inappropriate and inadequate mechanization as well as poor maintenance and operation of production equipment. Efficient loading and hauling operations are the backbone of mine production and productivity. Therefore, appropriate design and operation of loading and hauling systems are necessary to make progress towards optimal production and productivity. Load Haul Dumper (LHD), a loading and hauling machine for intermediate mechanization in underground mining, has seen instances of major breakdowns which are attributed to:

- Prevalence of bad managerial practices.
- Poor equipment maintenance and lack of real-time condition monitoring.
- Delay in timely response to identifying problems during the operation of the equipment.

As a result, these lead to frequent failures which decrease the percentage availability and utilization of machines and cause to minimize the production and productivity of machines. To get good profitability, among many factors, a mine needs to be operated with high levels of reliability and availability of its main production machinery.

1.4 DEFINITION OF THE PROBLEM

The proposed research work focuses on reliability improvement of LHD machines in underground mines by examining the myriad of parameters involved in its efficient operation/functioning. This may be achieved by addressing three independent goals, viz: by enforcing well-defined managerial practices to reduce the number of unscheduled failures; eliminate/reduce secondary damage resulting from the failure of any one component within a system; improve spare parts inventory control; and appropriate consideration of environmental factors associated with equipment performance. Further, to identify items, sub-assemblies of machines that need improvement in design needs to be identified, and design optimal maintenance policies to enhance reliability. Also, the availability and reliability of equipment in today's mining business needs special attention to reduce operational and capital costs to attain optimum profitability. 'Overall Equipment Effectiveness (OEE)' is needed to extract maximum profits from minimum investment in equipment and its operation. The main research problem addressed in this study can be stated as "Enhancement of the performance of LHDs by undertaking an analysis of reliability, availability, and maintainability (RAM) and by estimating the OEE.

1.5 OBJECTIVES OF THE PRESENT RESEARCH WORK

The principal objectives of the present research work are

1. Based on the field failure data obtained from underground mines, it is proposed to identify the impact of various influencing factors on the performance of LHD machines and to develop an outline for classification of field failure data and to perform further investigations such as reliability, Availability and Maintainability (RAM) analysis.

2. To estimate the Key Performance Indicators (KPIs) such as percentage of availability, utilization for identification of reasons for performance drop of the equipment.

3. To estimate the operational reliability of each sub-system for identification of its performance using the reliability prediction model and to develop reliability-based maintenance strategies for enhancement of expected equipment reliability during its useful life.

4. To estimate the overall system reliability and the remaining useful life of LHD systems using the Reliability Block Diagram (RBD) modelling technique. Further, identify the failure behaviour of a complex system, by assessing the component/ cut set contribution to system performance by adopting Failure Mode and Effective Analysis (FMEA) and Fault Tree Analysis (FTA) approaches.

5. To validate the computed results of Reliability, Availability and Maintainability with MATLAB based Artificial Neural Network (ANN), Fuzzy Interface System (FIS) predicted output responses for identification of accuracy in the results.

6. To estimate the Overall Equipment Effectiveness (OEE) of the system for identification of system performance.

1.6 FRAMEWORK OF THE THESIS

The entire research work is presented in this thesis in eight chapters and the brief contents are listed below.

Chapter 1 describes the introductory concepts includes a brief background of the current status of the mining industry in India followed by the status of underground coal and non-coal (metal) mines. Description of the LHD, and its contribution in underground mine production. The significance of reliability analysis, for performance improvement with examples of system/component failures, are highlighted. This chapter also contains the origin and scope of the research work, with a specific problem definition, research objectives, and framework of the thesis.

Chapter 2 provides a detailed literature review on addressed objectives in this thesis about the relevant concepts, theories, and practical studies.

Chapter 3 provides brief information on study areas to conduct field investigations for the collection of necessary field failure data of LHDs. This chapter also provides detailed information on research methodology, data collection, classification, and analysis.

Chapter 4 explains the "influencing factors" for the performance drop of LHDs by estimating the Key Performance Indicators (KPIs) such as availability percentage and utilization percentage. It also discusses the concept of operational reliability to identify the sub-optimal performance of each sub-system using Reliability Prediction (RP) approach. Further, the concept of a reliability-based maintenance optimization model is explained for enhancement of expected reliability during its useful life.

Reliability modelling is a method used to estimate or predict the system reliability prior to its execution and to analyze the failure behaviour of the system. Chapter 5 discusses the concept of operational reliability. This helps to identify the overall system reliability, remaining useful life of the equipment and influencing factors for performance drop of LHDs. The reliability modelling techniques used in operational reliability are Reliability Block Diagram (RBD), Fault Tree Analysis (FTA), and Failure Mode Effect Analysis (FMEA).

Chapter 6 validates the computed results of the RAM parameters of LHD machines with MATLAB based ANN predictions. This chapter also validates the estimated values of RPN in conventional FMEA with an advanced MATLAB based Fuzzy Interface System (FIS) to understand the risk prioritization of various breakdown modes.

Chapter 7 explains the methodology of Overall Equipment Effectiveness (OEE) of the system with necessary calculations of Key Performance Indicators (KPIs) of the percentage of availability and utilization and validated with world-class standards.

Chapter 8 discusses the many parameters of reliability studies of LHD and discusses the relevant conclusions, based on investigations carried out for Indian underground mines for maintaining the equipment effectively and efficiently. This chapter also addresses the limitations of present work and scope for future research in this area.

Present chapter focussed on introductory concepts of the mining industry and proposed machine for the research work. Also identified the problem statement, research objectives, and framework of the thesis. The preceding chapter provides the literature review on objectives addressed in this thesis about the relevant concepts, theories, and practical studies of past historical scientific studies on Reliability and LHD performance.

CHAPTER 2
LITERATURE REVIEW

2.1 PERFORMANCE OF THE EQUIPMENT IN WORK ENVIRONMENT

In the present global competitive business environment survival of the industries are more critical unless they produce their intended targets. Every industry is constantly looking for the enhancement of its economy and reputation by the increase of production and productivity. These are mainly dependent upon the effective utilization of men and machinery. In real-time situations, maintaining machinery with a higher level of reliability is also one of the crucial aspects (Military Handbook, 2003). Maintainable world-class performance of every industry regularly begins with a solid organization of activities that includes reliable assets, stable and repeatable production and work procedures and a well-trained and workforce. An observation of the historical records of Indian underground mines showed that the record of production and productivity over the past few decades is not encouraging, due to a wide variety of reasons such as improper managerial plan and organization, equipment performance and inefficient workforce (Sankha Sarkhel and Dey, U.K. 2015). Unavailability of the equipment in its working place is one of the major causes of performance drop. A higher level of availability gives scope to increase the production rate of capital intensive equipment by effective utilization (Santos. Amâncio., and António. Dourado. 1999). The percentage availability of machinery can be improved by reducing the probability of failure that can be achieved by improving the performance parameters of the equipment (Dhillon. B. S, 2008).

Reliability prediction and assessment play a key role in the performance evaluation of equipment. The performance of equipment mainly depends upon the reliability of usage, working atmosphere, the effectiveness of maintenance, operational procedures and technical skill of the operators, etc. Performance evaluation is helpful to organize better maintenance and production planning and to identify the early life failure of the system/sub-system (Oyebisi. T. 2000). Reliability analysis is the quantitative evaluation process of the products in the design and development phase. In different stages of the design phase, various methods have been used to evaluate the reliability index to provide the basis for finding the weak components and subsequently optimizing the sub-system/systems. The major ways of reliability analysis are divided into four categories such as Fault analysis, Reliability prediction, Acceleration test and Physics of Failure (POF) (Haowen. Mou. et al. 2013). The most frequently utilized approaches for reliability prediction are the Renewal Processes (RP), the Homogeneous Poisson Process (HPP) and the Non-Homogeneous Poisson Process (NHPP) (Barabady, J., and Kumar, U. 2008). It is more critical to develop an efficient reliability assessment technique for a complex repairable system, which usually have different failure mechanisms, to ensure adequate performance under extreme demands (Leangsuksun et al. 2003).

The reliability of a system usually depends upon a complex interaction of the laws of physics, engineering design, manufacturing processes, management decisions, random events, and usage. Hence, the improvement in reliability of a product is also often a complex process, involving many activities, including redesign, upgrading of materials and process improvements, as well as additional elements such as storage, handling and shipping (Shanshan Huo, 2014). When developing a technical system for a piece of unproven equipment, the designer is often required to come up with an initial reliability prediction for the new equipment as a basis for design decisions (e.g., configuration and redundancy). Reliability prediction often takes place or should take place in the early phase of the life cycle of a product. This would be the case, for example, in an analysis of systems where: (i) The product is complex, often involving new technology; (ii) Reliability is critical, with lack of reliability being very costly and possibly resulting in loss of life; (iii) Over design is highly undesirable, as it increases and highly inflates operating costs (Blischke. W. and Murthy. D. 2011).

2.2 FAILURE OF AN ENGINEERING SYSTEM

The term 'failure' is often confused with the terms *fault* and *error*. An *error* is defined as a discrepancy between a computed and observed or measured value or condition and the true, specified or theoretically correct value or condition. As an error is within the acceptable limits of deviation from the desired performance (target value), it is not necessarily (not yet) a failure. Failure is the event of termination of a required function and exceeds the acceptable limits (IEC, 1997). A *fault* is the state of an item characterized by the inability to perform a required function, excluding the inability during Preventive Maintenance (PM) or due to a lack of external resources. This means that a fault is a state resulting from the failure. The difference between failure, fault and error is shown in Figure 2.1 (Rausand. M., and Oien, K. 1996). Reliability is a characteristic of an item/component, expressed by the probability that the component will perform its required function to reach an adequate performance under given environmental conditions for a stated time interval (Tortorella. 2005).

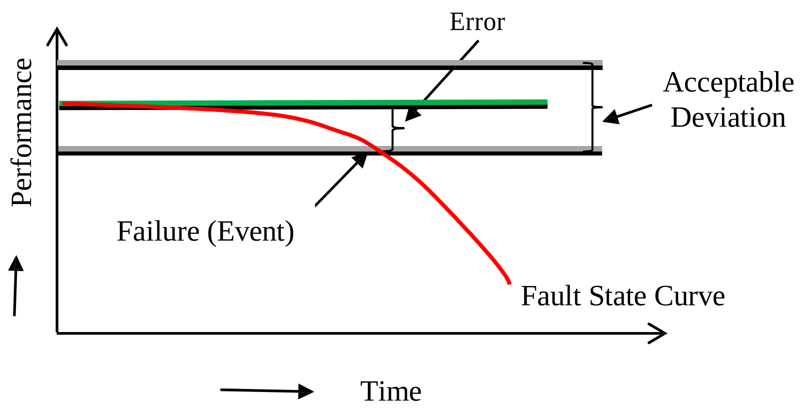


Figure 2.1 Difference between failure, fault and error

2.3 CAUSES FOR OCCURENCE OF SYSTEM FAILURE

It is very essential to have an understanding about the causes of occurrence of an engineering system failure. According to Naikan, V. N. A. (2009), failure of a system or component is the inability of a system or component to deliver its intended function satisfactorily, it may be either partial or complete. It is necessary to start the analysis with a clear objective or definition, preferably in quantitative terms to avoid confusion in all the stages. The system or component is experienced by failure due to a wide variety of causes. Out of these, some of them are known causes and others are unknown due to many reasons. The detailed explanations of an engineering system failure are given in Table 2.1.

Table 2.1 Reasons for an engineering system failure (Naikan, V. N. A. 2009)

Sl.No	**Reasons for Breakdown**	**Detailed Explanation**
1	Poor design	Wrong materials, dimensions and tolerances, stress concentration, inadequate interface design
2	Incorrect manufacturing	Usage of outdated technology and old machines, lack of control over the process, lack of calibrated instruments, inadequate training
3	Inadequate Inspection/testing	Adoption of incorrect inspection procedures, lack of technical knowledge to test to produced components and inadequate management of models for quantification.
4	Complexity	Number of components and interconnections, more number of interfaces
5	Improper Maintenance	Under- and over-maintenance, wrong tools and methods, poor spare parts management
6	Raw material supply	Poor vendor evaluation and inadequate screening of materials, lack of understanding of suppliers.
7	Quality assurance	The low process capability of machines, inadequate quality control, inadequate instruments and training.
8	Packaging, shipping, Transportation	Road, rail, air, water transportation requires special packaging with shock resistance and environmental protection.
9	Improper installation	Improper foundation, excessive vibration, bad quality accessories, usage of wrong tools and methods
10	Operational Instruction	Wrong instruction, lack of clarity, difficult to understand, the poor language of manual.
11	Human error	Lack of understanding of process and equipment, carelessness, poor judgmental skill, physical disability.

2.4 COLLECTION AND EVALUATION OF FAILURE DATA

2.4.1 Data Collection, Classification and Manipulation

Three steps must be performed before the data can be analyzed. These are data collection, data classification and data manipulation. How maintenance data is collected and organized will reflect the depth and breadth of the study. The completeness of the raw data will ultimately determine the type of analysis which can be performed (Bala, J., et al. 2018). Data collection plays an important role in a research study of any kind. The impact of incorrect data collection can cause the results of the whole research study to be illogical. The scale of data collection methods is very wide-ranging from quantitative methods to qualitative methods. Table 2.2 describes some important data collection methods (Archer. T. M. 1988).

Generally, in the mining industry, there is a separate department known as the Engineering Department to maintain the complete information/data of the machinery. Both maintenance and operational data are available in both soft and hard copy formats in the form of computerized records and day to day activities entered in the logbook. In addition to that, real-time monitoring can also be conducted during the operation of the vehicle in the work environment to identify the potential failure modes, reasons for the occurrence of failures, etc. The available machine hours in a day were classified into three numbers of shifts to perform the specified job/task. The number and type of each failure mode were noticed in each shift to perform the repair or replacement action. After successful completion of the data collection, the categorization of datasets has also been made based on the type of failure mode (Balaraju, J., et al. 2017). Probability and statistical techniques are useful to analyze the data sets after the data collection. These techniques are helpful to identify the 'best fit distribution' as well as validate the assumption of Independent and Identically Distributed nature (IID) of the data sets.

Table 2.2 Descriptions of some of the data collection methods (Archer. T.M, 1988).

Sl.No	Collection Method	Descriptions
1	Behavior Observation	A list of actions among participants being observed. A tally is kept for each behavior or action observed.
2	Knowledge Tests	Information about what a person already has learned.
3	Opinion Surveys	An assessment of how a person or group feels about a particular issue.
4	Performance tests	Testing the ability to perform or master a particular skill.
5	Self-Ratings	A method used by participants to rank their performance, knowledge, or attitudes.
6	Questionnaire	A group of questions that people respond to in writing.
7	Time Series	Measuring a single variable consistently over time, i.e. daily, weekly, monthly, annually.
8	Case Studies	Experiences and characteristics of selected persons involved.
9	Individual Interviews	Individual’s responses, opinions, and views.
10	Group Interviews	Small groups’ responses, opinions, and views.
11	Wear and Tear	Measuring the apparent wear or accumulation on physical objects, such as a display or exhibit.
12	Physical Evidence	Residues or other physical by-products are observed.
13	Panels, Hearings	Opinions and ideas.
14	Records	Information from records, files, or receipts.
15	Logs, Journals	A person’s behavior and reactions recorded as a narrative.
16	Simulations	A person’s behavior in simulated settings.
17	Advocate Teams	Ideas and viewpoints of selected persons.
18	Judicial review	Evidence of actions assessed by a jury of professionals.
19	Inspections	Real-time monitoring during the operations.

2.5 REQUIREMENT OF RELIABILITY INVESTIGATION

Reliability estimation plays a key role in the performance evaluation of any kind of a simple or complex system. The performance of equipment mainly depends upon the reliability of the usage, working atmosphere, and effectiveness of maintenance, operational procedures, and technical skill of the operators (Bala, J., et al. 2018). These performance forecasts help to organize the maintenance and production planning, reliability assessment and can also be used to detect a fault in the production system for the risk evaluation process (Oyebisi. T. 2000). Some of the most frequently utilized approaches for simple or complex repairable failure systems in reliability analysis are: the Renewal Processes (RP); the Homogeneous Poisson Processes (HPP) and the Non-Homogeneous Poisson Processes (NHPP) (Lindqvist. B. H 2006). Navas. M. A. et al. (2017), have applied the concepts of stochastic modelling to the electric traction systems of 23 numbers of trains and 40 numbers of escalators for an operating period of 10 decades in a railway sector to find out the impact of the intermittent breakdowns on the Time Between Failure (TBF) for HPP and NHPP hypothesis rejection. Failure rate $\lambda(t)$ of a repairable system can be anticipated using stochastic analysis for the consecutive TBFs. If the TBF data sets exhibit trend free nature and these are exponentially distributed, where $\lambda(t)$ is constant, then the HPP modelling method is suggested for further analysis. On the other hand, if a trend exists in the data sets then the analysis has been carried out with the NHPP model and the parameters were estimated with the application of Power Law Process (PLP) analysis (IEC 60300-3-5 ed1.0. 2001). If there is no existence of a trend in the data sets, then the reliability analysis has been carried out using renewal process modelling and the parameters were estimated using statistical (statistic U test) analysis (IEC 60605-6 ed3.0. 2007 and IEC 61710 ed2.0. 2013). Reliability forecasts are necessary for all kinds of repairable systems/equipment to identify the life of the equipment and to estimate its remaining useful life (Jardine. A. K. S. 1988). The downtime period of the equipment is usually considered as input data to reliability analysis. This downtime can be of both breakdown/ failure time and the idle time of the equipment. In some of the cases, repair time of the breakdown component/ equipment can be used as the input resource in reliability growth analysis (Ross. S. M. 1971 and O’Connor. P. D. T

1991). The reliability of a repairable system can be enhanced by applying proper maintenance strategies. In modern quality management, accurate predictions are desirable for physical systems (machinery) to fulfill the required standards. A repairable system is usually defined as one which can be repaired to recover its functions after each failure rather than be discarded (Coe, C. K. 1981). "Failure" means that the component fails to meet its required performance criteria within a specified time. This "failure" will naturally lead to a need for maintenance. When "repair" is mentioned, it usually includes "replacement". It is important to predict the reliability of complex systems accurately, especially during long periods of operation. A company can plan its production with an optimal level of maintenance staffing, inventory and budget, following the prediction of remaining useful life.

At present stochastic/statistical techniques and renewal process models are most commonly used methods to model the complex repairable systems (Barabady, J., and Kumar, U. 2005) and the methods are like: the Poisson point process (Kim. Y. H 1989, Knowles, W. 1994 and Kumar. U et al. 1989); Bayesian method (Nick. Vayenas. Sihong. Peng. 2014); Proportional Hazard Model (PHM) (Blischke. W. and Murthy. D. 2011) and combinations of these models (Hall. A and Daneshmend. L. K 2003). These different models address the reliability prediction of a repairable system and have been applied in different scenarios. However, the following two major drawbacks have affected the effectiveness of these existing models. The first drawback is that of being unable to model comprehensively the different states of repairable systems after having multiple repairs. After performing these repair or maintenance actions the repairable system can be treated in "as good as new" condition (Bloch. Mercier. 2002). The second drawback is that existing models often treat a repairable system as a "black box", without considering the individual contributions of different components (Mandal. S. K 1996).

From the classical engineering approach, reliability is defined as the ability of a system or component to perform its specified job/task under stated conditions/period (Moss. T. and Andrews. J. D 1996). The present investigation has been performed to evaluate the breakdowns, to identify the major reasons for the occurrence of breakdowns and frequency of occurrence, to locate the significant subassemblies and to develop the models to forecast the reliability percentage of sub-systems/systems.

2.6 RELIABILITY, AVAILABILITY AND MAINTAINABILITY (RAM)

In many of the industrial sectors, the complex mechanized systems are prone to uneven occurrence of frequent breakdowns due to improper and inefficient operational and maintenance practices. Hence, there is a requirement to take the remedial measures/actions to reduce the breakdowns and to ensure the smooth operation (Farr, J. V. 2011). A detailed Reliability, Availability and Maintainability (RAM) analysis plays an important role in the analysis of a complex system (Knowles, W. 2010). According to Ram Prasad Choudhary. (2015) RAM analysis has become more significant in recent years due to the presence of large number of competitors; willing to provide quality goods and services, growing needs of consumers and strategies to minimize overall operating costs. RAM analysis of mining machinery is very essential for ensuring smooth production. When the systems are having the least percentage of reliability level, then there is a need to take the necessary actions to improve the percentage. This can be improved by reducing the failure rate or increasing the repair rate for the components or systems (Samanta. B. et al., 2004). RAM analysis is capable of optimizing the equipment units of each sub-system to avoid failures and increase reliability. Understanding the scientific basis of RAM needs knowledge of probability and statistics.

2.6.1 Probability and Statistics

Probability and statistics are two interconnected concepts and covers the independent theoretical descriptions. Statistical analysis is regularly used in probability distribution functions. However, probability theory consists of mathematical relationships and these are not directly related to the concepts of statistics (Naikan. V. N. A. 2009).

Probability is the branch of mathematics that studies the possible outcomes of given events together with the outcomes' relative likelihoods and distributions. In general, probability is used to mean the chance that the set of events are expressed on a linear scale from 0 to 1 (i.e., impossibility to certainty state) or expressed in percentages between 0 to 100%. The analysis of events governed by probability is called statistics. Statistics is a discipline that allows investigators to evaluate conclusions derived from sample data. This scientific approach (statistics) is utilized for (Myers. E et al. 2012):

- Data collection.
- Understanding and investigation of the collected data.
- Assess the reliability of conclusions based on sample data.

2.6.2 Probability Density Function (PDF)

Probability density function (PDF) is a statistical measure that defines a probability distribution for a random variable and is often denoted as f(x). Let X be a continuous random variable (Myers. E et al. 2012). Then a probability density function (PDF) of X is a function f (x) such that for any two numbers a and b with a ≤ b,

$$P(a < \quad < \quad) = \int_{a}^{b} f(x)dx \qquad (2.1)$$

That is, the probability that X takes on a value in the interval [a, b] is the area above this interval and under the graph (Figure 2.2) of the density function. The graph of f(x) is often referred to as the density curve. As probabilities should not be negative and never greater than 1, the following two properties (Equation (2.2) and (2.3)) of the PDF are always true (Myers. E et al. 2012):

$$\int_{-\infty}^{\infty} f(x)dx = 1 \qquad (2.2)$$

$$f(x) \geq 0 \qquad (2.3)$$

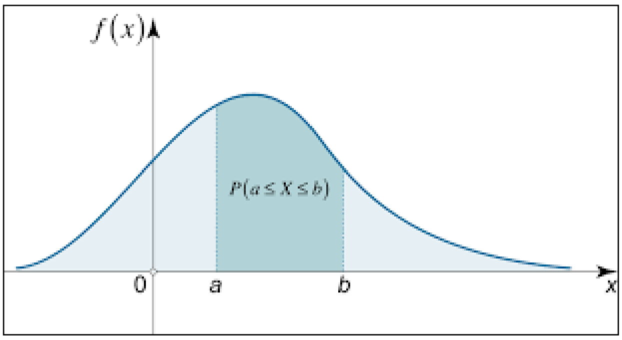


Figure 2.2 Probability density function graph

2.6.3 Cumulative Distribution Function (CDF)

A function that gives the probability of a random variable is less than or equal to the independent variable of the function. For a random variable X, the CDF is the function F(x), defined by (Myers. E et al. 2012):

$$F(x) = P(X \leq x) = \int_{0}^{x} f(x)dx \qquad (2.4)$$

Where X denotes the random variable, which is the sum or integral of the PDF of the distribution and x denotes the independent variable.

2.6.4 Reliability

According to Rausand. M and Oien. K (1996), reliability is a measure of the ability of equipment to operate without failure when put into service. A more rigorous definition of reliability is as follows: reliability of a component (or a system) is the probability that the component performs its intended function adequately for a specified period without a major breakdown under the stated operating conditions or environment (Alka Munjal and S. B. Singh, 2014). Reliability can also be defined as the probability that the system will perform satisfactorily for a given period when used under specified operating conditions (Esmaeili. M and Aghajani. A, 2011). This definition brings into focus four important factors for determination and assignment of reliability, namely,

- The reliability of a system is expressed as a probability
- The system is required to give adequate performance
- The duration of the adequate performance is specified
- Environmental and operating conditions are prescribed.

The reliability function for the constant failure rate of an exponential function is expressed in Equation (2.5) as follows:

$$(\quad) = \quad {}^{-\lambda t} \qquad (2.5)$$

Where e is the base of natural logarithms which equals 2.718 and λ is the failure rate (1/MTBF) and t is the time to failure. The basic fundamental terms of reliability are given in Table 2.3.

Table 2.3 Fundamental terms connected to Reliability **(**Stamatis, D. H. 2003)

Reliability Measure	**Description**
Failure	An event, or inoperable state, in which any item or part of an item does not, or would, not, perform as previously specified.
Failure rate	The expected rate of occurrence of failure or the number of failures in a specified period. The failure rate is typically expressed in failures per million or billion hours.
Mean Time Between Failures (MTBF)	The number of hours to pass between failures. MTBF is typically expressed in hours.
Mean Time To Failure (MTTF)	Expected time to failure for a system that is not repairable. Once a failure occurs, the system cannot be used or repaired
Mean Time To Repair (MTTR)	It is the expected period from failure (or shut down) to the repair or maintenance completion. This term is typically only used with repairable systems.

As mentioned above the reliability, R(t), of the component is the probability of a component surviving to a time *t* and is expressed as Equation (2.6):

$$R(t) = \int_t^{\infty} f(t)\, dt \qquad (2.6)$$

Where f(t) is the probability density function (PDF) of the random variable and t is the time to failure.

Based on the rate at which failures occur in the interval t_1 to t_2, the failure rate, $\lambda(t)$, is defined as the ratio of the probability that failure occurs in the interval. It is assumed that failure does not happen before time t_1. Mathematically, the failure rate is expressed as the ratio of failure time at the starting point to the total time length of the interval (Equation 2.7).

$$\lambda(t) = \frac{(\quad) - (\quad + \Delta \quad)}{\Delta \quad \Delta \quad (\quad)} \qquad (2.7)$$

The failure rate can, therefore, be defined as the probability of failure in unit time of a component that is still working satisfactorily. The term unreliability is defined as the probability that a failure has occurred in a specified period, T and is equal or smaller than operating time t. This is same as that of CDF and is expressed as (Elsayed. E. A 2012):

$$(\quad) = \quad (\quad \leq \quad) \qquad (2.8)$$

$$(\quad) = \int_0 \quad (\quad) \qquad (2.9)$$

A common graphical interpretation of the failure rate is shown in Figure 2.3. This model is known as the “bathtub” curve and was initially developed to model the failure rates of mechanical equipment (Pulcini. G. 2001 and Coetzee. J. L. 2004). The mean-time to failure curve/Bathtub curve indicates that a new machine has a high probability of failure because of installation problems during the first few weeks of operation. After this initial period, the probability of failure increases sharply with the elapsed time (Mobley, K. 2002). The failure rate is theorized to be high at the start, dropping off as the weaker devices fail early. The failure rate then approaches a constant as the components enter their useful lifetime. Failures in this period can be attributed to the random overload of the components. Finally, wear-out occurs and the curve increases sharply.

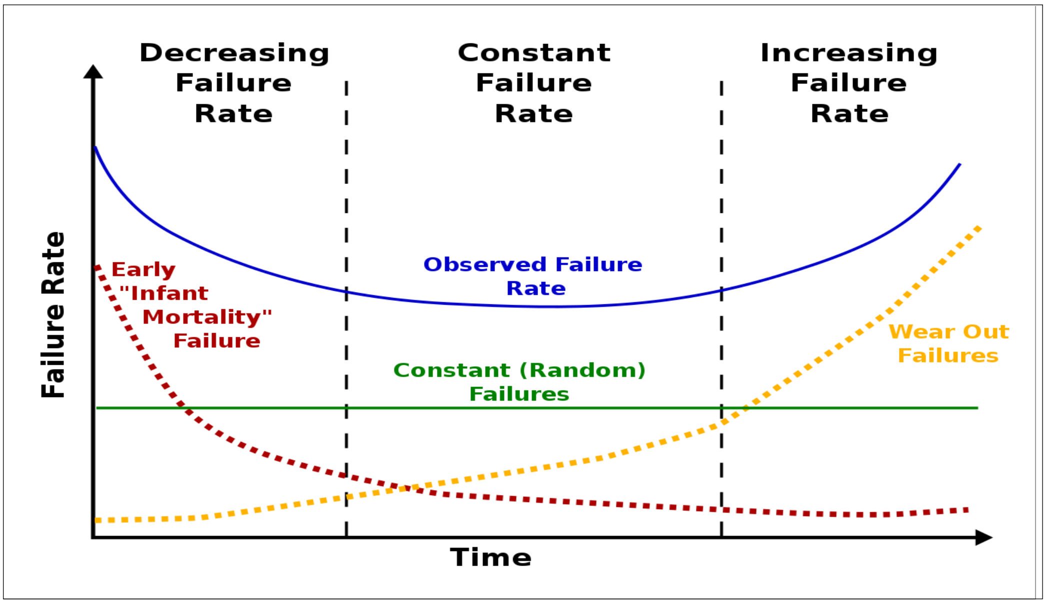


Figure 2.3 Bathtub curve

2.6.5 Availability

The term availability is defined as the ability of an item/equipment/system to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided (Mousa. Mohammadi. et al. 2015). According to Ebeling, C. E. (1997), availability is defined as the probability of a system to perform its intended task in a specified period when maintained and operated in a prescribed manner.

According to Sukhwinder Singh Jolly Bikram Jit Singh (2014), availability is defined as the available percentage of the machine to perform its specified task at its working face. The percentage availability of the machine may also be defined as the ratio of available machine hours to the shift scheduled hours. While calculating the percentage availability, shift scheduled hours are taken as total scheduled hours for a considerable period of equipment's operation. If any extra hours of work beyond the shift exist, these can be added to the total scheduled hours. The idle period of less than or equal to 15 minutes can be ignored. Percentage availability also facilitates information about the effectiveness or efficiency of different maintenance practices. This information is of added value to the management by knowing how machine availability would vary by varying the scheduled shift hours.

Percentage availability helps in judging and comparing the efficiency of the maintenance departments of different units. This can also assist the management in knowing how the availability of machines would change by changing the scheduled shift hours of work. The percentage availability of machines would change by changing the scheduled shift hours of work (Arputharaj M. E. M, 2015).

Availability is the probability that equipment will be in an operable and committable state at the commencement of work/operation and the operation of equipment is expressed in a random time. Mathematically, it can be expressed as the ratio of uptime to the uptime plus downtime of the equipment (Castro, H. F., and Cavalca, K. L. 2006).

$$\text{Availability (A)} = \frac{\text{Life time}}{\text{Total time}} = \frac{\text{Life time}}{\text{Life time} + \text{Repair time}}$$
$$= \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \qquad (2.10)$$

Where, MTBF is the Mean Time Between Failures, the inverse of the failure rate and MTTR is the Mean Time To Repair, the inverse of the repair rate.

According to Hoseinie. S. H et al. (2012), a wide variety of availabilities such as point wise, interval and limiting or steady-state are used for performance assessment of any kind of machinery. Steady-state or limiting availability is the most practical one to use in many of the engineering applications.

Steady-state or limiting availability: It is the mean of the instantaneous availability under steady-state circumstances over a given time period. Under certain operating conditions, for instance, constant failure rate and repair rate, the steady-state availability may be expressed by the ratio of the mean time between failure to the summation of mean time between failure and mean time to repair. Under these conditions, asymptotic and steady-state availability are identical and often simply referred to as availability. The steady-state availability or limiting availability of a system is defined as:

$$= \lim_{a \to \infty} (\quad) \qquad (2.11)$$

Where A denotes the steady-state or limiting availability and A(t) denotes the mean availability at a given time period, ‘t’. This quantity is the probability that the system will be available after it has been run for a long time, and is a very significant measure of performance of a repairable system. According to Hoseinie, S. H (2011), based on definitions of uptime and downtime, the steady-state availability can be divided into the following categories:

- **Inherent availability:** Inherent availability is the probability that a system or equipment, when used under stated conditions, in an ideal supporting environment (i.e., readily available tools, spares, maintenance personnel, etc.), will operate satisfactorily at any point in time as required (Walliman. N. 2011). It excludes preventive maintenance action, logistic delay time, administrative delay time, and is expressed as (Leitch. D. 1995):

$$\mathrm{Ai} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR}} \qquad (2.12)$$

  Where MTBF is the mean time between failure and MTTR is mean time to repair. Inherent availability is based solely on the failure distribution and repair time distribution (Walliman. N. 2011).

- **Achieved availability**: Achieved availability is the probability that a system or equipment, when used under stated conditions in an ideal supporting environment (i.e., readily available tools, spares, personnel, etc.), which will operate satisfactorily at any point in time. The achieved availability is defined as (Walliman. N. 2011):

$$\mathrm{Ac} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTBM}} \qquad (2.13)$$

Where MTBF denotes the mean time between failure and MTBM denotes the mean time between maintenance operations. The MTBM includes both preventive maintenance and mean active maintenance time (MAMT). If it is performed too frequently, Preventive Maintenance (PM) can have a negative impact on the achieved availability even though it may increase the MTBF. PM time intervals resulting in frequent downtimes have availability less than the inherent availability.

As the PM interval increases, the achieved availability will reach a maximum point and then generally approach the inherent availability.

- **Operational availability**: It is the probability of a system when used under stated circumstances in an actual operational environment, will operate satisfactorily when called upon. The operational availability is defined as (Walliman. N. 2011):

$$\mathrm{Ao} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MDT}} \qquad (2.14)$$

Where MDT is the mean maintenance downtime and includes maintenance time (M), logistics delay time and administrative delay time. The availability of a system is a complex function of reliability, maintainability and supply effectiveness. This can be expressed as (Blanchard and Benjamin. S 2004):

$$\mathrm{As} = \mathrm{f}(\mathrm{Rs}, \mathrm{Ms}, \mathrm{Ss}) \qquad (2.15)$$

Where, As= system availability, Rs= system reliability, Ms= system maintainability and Ss= supply effectiveness.

2.6.6 Maintainability

Maintainability is “the ability of an item/equipment/system under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function when maintenance is performed under given conditions and using stated procedures and resources” (Dhillon, B. S. 2008).

Maintainability is also defined as the probability that an item or system will be restored to specified conditions within a given period when maintenance action is taken under the prescribed procedures and resources. MTBF and MTTR help to evaluate the metrics of maintainability and failure rate. As the failure rate (Equation 2.17) increases then the corresponding percentage of reliability of the system decreases. The rate of reliability and failure rates are inversely proportional. If we want to improve the system reliability then there is a definite need to reduce the failure frequency. Maintainability is used for estimating the maximum corrective maintenance time for system repair actions (Wynholds. H. W and Skratt. J. P. 1977). The probability of repair (maintainability) in a specified time (t) can be estimated with Equation 2.16:

$$Maintainability\ (Mw) = 1 - e^{-\left(\frac{MTTR}{\eta}\right)^{\beta}} \qquad (2.16)$$

$$\text{Failure rate } (\lambda) = \frac{1}{\text{MTBF}} \qquad (2.17)$$

Where, MTBF = mean time between failure, MTTR = mean time to repair, η=scale parameter and β=shape parameter.

There are three types of maintenance actions available for a repairable system namely corrective maintenance, preventive maintenance, and inspection (Naikan. V. 2009).

Corrective Maintenance (CM): In this CM, a set of maintenance actions are performed after the occurrence of a failure of the system. These actions help to restore the system to its original or operating state. These actions are the typical repairs or replacement of components or subsystems and are performed randomly as failure times are not possible to know in advance.

Preventive Maintenance (PM): In this PM a set of maintenance actions are performed before the failure of the system. These actions can be of many types that are typically component repairs, lubrication, and overhauls. For PM to be necessary and beneficial, two conditions have to be satisfied. Firstly, the system or component has to experience wear-out, implying an increasing failure rate. Secondly, the overall cost of PM actions has to be less than the overall cost of CM actions.

Inspections determine the hidden or future failures. The inspection techniques can be of many types and consist of both visual and non-visual techniques. Inspections do not alter the condition or age of the equipment, as no repair or replacement takes place. An inspection can lead to repair or replacement decisions, but in that case, the repair is either classified as CM or PM.

The nature of maintenance is further categorized into a variety of categories such as condition-based maintenance, periodic maintenance, design-out maintenance, and opportunity maintenance. These categories are used in wide variety of practical applications in real time. The selection of maintenance strategy is made by assessing the probability of failure and its effect on health, safety, environment, production and quality (Nakajima. S. 1988).

2.7 PROBABILITY DISTRIBUTION FUNCTIONS

Statistical distributions have been formulated by statisticians, mathematicians and engineers to mathematically model or represent certain behaviour of an equipment failure among many other applications, in various domains. These statistical distributions are useful to carry out the subsequent life data analysis. Reliability Life Data Analysis refers to the study and modelling of observed equipment lives (Bala. J et al. 2018). These lifetimes can be measured in hours, miles, cycles-to-failure, stress cycles or any other metric with which the life or exposure of equipment can be measured. There is a wide variety of probability distribution functions or life-time distributions such as Exponential, Weibull, Lognormal, Normal and Gamma that can be used to model the reliability data. The present study uses four common probability distribution functions for the reliability analysis. The mathematical representations of these four functions are explained as follows (ITEM Software, 2007):

2.7.1 The Exponential Distribution

The exponential distribution is commonly used for components or systems exhibiting a *constant failure rate*. Due to its simplicity, it has been widely employed, even in cases where it doesn't apply. In its most general case, the 2-parameter exponential distribution is defined by (Myers. E et al. 2012):

$$f(t) = \lambda e^{-\lambda(t-\gamma)} \qquad (2.18)$$

Where, λ is the constant failure rate per unit of measurement (e.g., failures per hour, per cycle, etc.) and γ is the location parameter. Besides, the failure rate can be expressed as:

$$\lambda = \frac{1}{M} \qquad (2.19)$$

Where MTBF is the mean time between failure.

If the location parameter, γ is assumed as zero, then the exponential distribution becomes the 1-parameter only and is expressed as (Equation 2.20):

$$(\;) = \lambda \quad ^{-\lambda}$$

(2.20)

2.7.2 The Weibull 3-Parameter Distribution

The Weibull distribution is widely used in reliability and life data analysis due to its versatility. Depending on the values of the parameters, the Weibull distribution can be used to model a variety of life behaviours. The values of the shape parameter, α, and the scale parameter, β, affect such distribution characteristics as the shape of the curve, the reliability, and the failure rate. In its most general case, the 3-parameter Weibull PDF is defined by Equation 2.21(Myers. E et al. 2012):

$$(\ ) = -\frac{}{\eta} \times \left\{\frac{-}{\eta}\right\}^{\beta-1} \times {}^{-\left\{\frac{t-}{\eta}\right\}} \qquad (2.21)$$

Where η is the scale parameter, β is the shape parameter, γ is the location parameter and t is the time duration.

2.7.3 The Weibull 2-Parameter Distribution

If the location parameter, γ is assumed to be zero, then the distribution becomes 2-parameter Weibull and is mathematically expressed as (Equation 2.22) (Myers. E et al. 2012):

$$(\ ) = \frac{-}{\eta} \times \left\{\frac{-}{\eta}\right\}^{\beta-1} \times {}^{\left\{\frac{t}{\eta}\right\}} \qquad (2.22)$$

2.7.4 The Weibull 1-Parameter Distribution

One additional form is the 1-parameter Weibull distribution, which assumes that the location parameter, γ is zero, and the shape parameter is a known constant, or   is constant denoted by C, so mathematically it can be expressed as (Equation 2.23) (Myers. E et al. 2012):

$$(\ ) = \frac{-}{\eta} \times \left\{\frac{-}{\eta}\right\}^{-1} \times {}^{-\left\{\frac{t}{\eta}\right\}} \qquad (2.23)$$

2.7.5 Parameters in Life Data Distribution

Distributions can have any number of parameters. As the number of parameters increases, so does the amount of data required for a proper fit. In general, the lifetime distributions used for reliability and life data analysis are usually limited to a maximum of three parameters. These three parameters are usually known as the *scale parameter*, the *shape parameter* and the *location parameter (*Bala, J et al. 2018).

Scale Parameter (η): The scale parameter is the most common type of parameter. All distributions in this reference have a scale parameter. In the case of one-parameter distributions, the sole parameter is the scale parameter. The scale parameter defines where the bulk of the distribution lies, or how stretched out the distribution is. In the case of the normal distribution, the scale parameter is the standard deviation.

Shape Parameter (β): The shape parameter, as the name implies, helps define the shape of a distribution. Some distributions, such as the exponential or normal, do not have a shape parameter since they have a predefined shape that does not change. In the case of the normal distribution, the shape is always the familiar bell shape. The effect of the shape parameter on distribution is reflected in the shapes of the PDF, the reliability function and the failure rate function.

Location Parameter (γ): The location parameter is used to shift distribution in one direction or another. The location parameter, usually denoted as γ, defines the location of the origin of distribution and can be either positive or negative. In terms of lifetime distributions, the location parameter represents a "time-shift".

This means that the inclusion of a location parameter for a distribution whose domain is normally $[0, \infty]$will change the domain to $[\gamma, \infty]$ where γ can either be positive or negative. This can have some profound effects in terms of reliability. For a positive location parameter, this indicates that the reliability for that particular distribution is always 100% up to that point. In other words, a failure cannot be occurred before this time γ. Many people are uncomfortable with the concept of a negative location parameter, which states that failures theoretically occur before time zero. Realistically, the calculation of a negative location parameter is indicative of quiescent failures (failures that occur before a product is used for the first time) or of problems with the manufacturing, packaging or shipping process. More attention will be given to the concept of the location parameter in subsequent discussions of the exponential and Weibull distributions, which are the lifetime distributions that most frequently employ the location parameter (ITEM Software 2007).

Level of Significance (ε): The most widely used non-parametric test for assessing the goodness-of-fit of repair times and times between failures is the Kolmogorov-Smirnov (K-S) test (Navas, M. A., et al. 2017). The K-S test examines for differences between the theoretical distribution and the observed cumulative distribution. This is achieved by determining the largest absolute difference between a theoretical distribution and a random sample of size, n. To determine a maximum acceptable limit of this difference, a level of significance (ε) is applied to the test. The larger the value of epsilon (ε), the more likely the hypothesis will be accepted. This test can easily be performed using a probability distribution fitting software package (ITEM Software 2007).

2.8 RELIABILITY PREDICTION OF A REPAIRABLE SYSTEM

Quantitative reliability analysis techniques uses the real-time failure data (obtained, for instance, from a test program or field operations) in conjunction with suitable mathematical models to produce an estimation of system reliability. Three stochastic processes are generally used for reliability analysis of repairable systems (Hoseinie. S. H. et al. 2012):

- Homogeneous Poisson process (HPP);
- Renewal process (RP); and
- Non-homogeneous Poisson process (NHPP).

To determine which process is the best analysis method for available data, one must perform the trend and serial correlation tests to determine whether the data are Independent and Identically Distributed (IID) or not. Regarding results of the trend analysis, if the assumption that the data are identically distributed is not valid, then classical statistical techniques for reliability analysis may not be appropriate; therefore, a non-stationary model such as NHPP must be fitted. The presence of no trend and no serial correlation in failure data reveals that the data are IID and therefore the classical statistical techniques are the best way for reliability modelling. The trend test can be performed both analytically and graphically (Hoseinie, S. H. et al. 2012 and Kumar. U 1990). There are five analytical methods that are used for testing the presence of trend, such as Reverse Arrangement Test, Military Handbook

Test, Laplace Test, likelihood-ratio test and Area Test. Military Handbook (NHPP-Power Law Process (PLP) model)Test is one of the applicable analytic tests for finding significance when the choice of datasets are in trend. This test checks the trend presence by calculating the test statistic U (Equation 2.24) (Kumar. U 1990):

$$\{ = 2\sum_{i=1}^{n} \ln \frac{n}{i} \} \qquad (2.24)$$

Where n is a total number of failures, T_n is the time of the n^{th} failure and T_i is the time of the i^{th} failure. Under the null hypothesis of an HPP, the test statistic U is chi-squarely distributed with 2(n-1) degrees of freedom. If the null hypothesis is rejected at 0.05 level of significance, it means that the TBFs data has a trend and therefore and are identically distributed (Hoseinie, S. H. et al., 2012).

In graphical methods, the trend test involves plotting the cumulative failure numbers against the cumulative time to failure. If the plotted points lie (or approximately) on a straight line, then the data are in trend and identically distributed. A test for serial correlation was also done by plotting the i^{th} TBF against the $(i-1)^{th}$ TBF, i = 1, 2,..., n. If the plotted points are randomly scattered without any pattern, it means that there is no correlation among the TBFs data and the data are independent. The statistical method called Chi-Squared test is frequently used methodology for validation of the data sets as well as for identification of the reliability model. Kolmogorov–Smirnov (K-S) test is classically used for the selection of the best-fit/goodness of fit distribution. Further, the reliability analysis of complex repairable systems should perform based on the determined reliability modelling method (Kumar. U and Kelefsjö. B 1992).

2.8.1 Approach for Reliability Analysis

The reliability characteristics of equipment can be determined from the systematic analysis of reliability prediction with the utilization of time between failure (TBF) and time to repair (TTR) data. The step-by-step procedure of reliability modelling of a repairable system is given in Figure 2.4. This detailed flowchart can help to model the datasets and is used as a base for failure and repair data analysis.

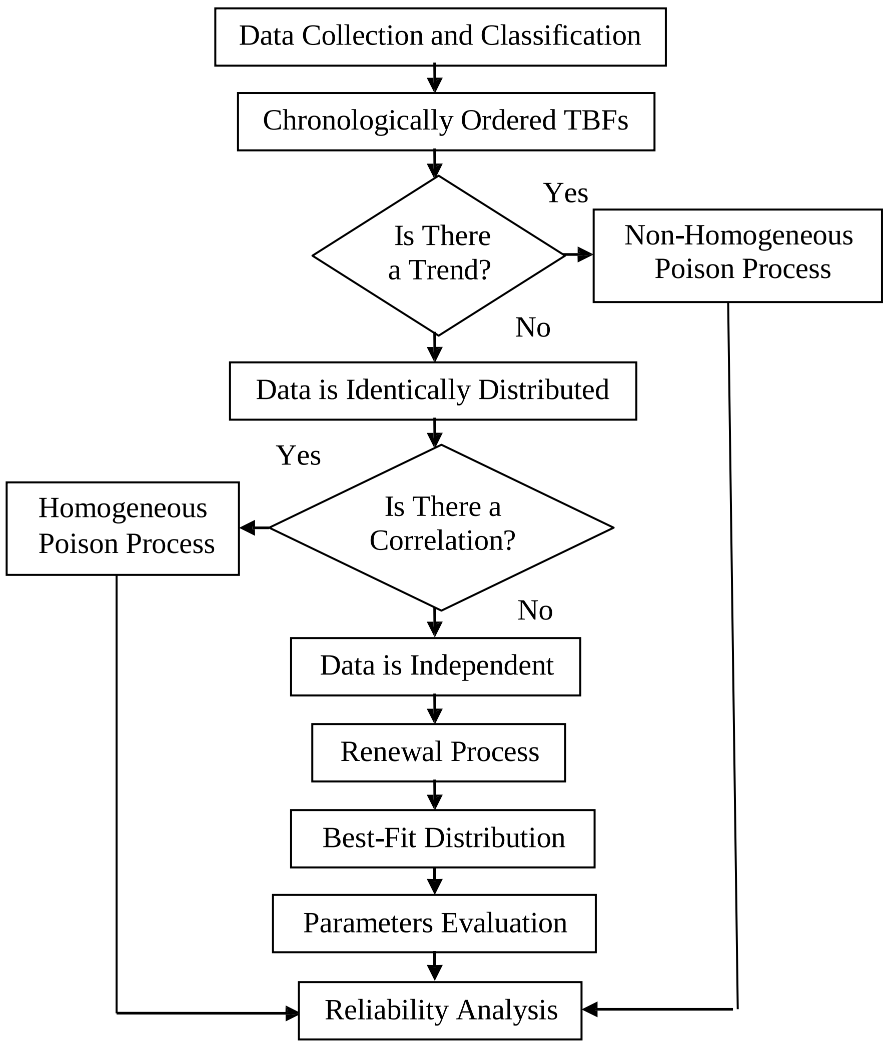


Figure 2.4 Flowchart for reliability prediction of repairable systems

2.8.2 Independent and Identical Distribution (IID) Assumption

Simple graphical techniques are used for verifying the Independent and Identically Distributed (IID) assumption for the failure data sets of a system. These tests are used to test or identifies the existence of trends or structures in the field failure data (TBFs). If the data sets do not fulfill the IID requirement, then the probability distribution functions are used to model the data sets (Kumar. U. et al. 1989). The assumption that the data sets are independent means, current failure is not dependents on the previous one and that implies parameters of the chosen distribution do not change with respect to time. The assumption that the data sets are identical means, different data set points follows the similar kind of distribution.

Since the assumption of IID is normally not valid (Aven. T. 1985), proper tests should be used to test for the presence of structures or trends in the failure data (the TBFs). If there is no trend in the data, the assumption of identical distribution for the TBFs under consideration is not contradicted. It is also important to test the successive interracial times for independence by testing them for serial correlation. The graphical methods are used for testing the presence of trend and serial correlation in our data. Non-linear Homogeneous Poison Process (NHPP) is used for modelling the data sets, instead of probability distribution, when the IID requirement is not fulfilled (Kumar. U. et al. 1990). The trend test can verify the independent assumption and the serial correlation test can verify the identical assumption, with the graphical plots.

2.8.3 Trend Test and Serial Correlation Test

Two common graphical methods are used for assessing the sample data, these are the trend test and the serial correlation test. Trend test is used to determine the presence of trends in the failure patterns of an equipment. Trend test involves plotting the cumulative failure frequencies (CFF) against the cumulative time between failures (CTBF) (Law. A. M and Kelton. W. D. 1991). The shape of the trend plot will reveal the information that the piece of equipment is experiencing a decreasing failure rate (improving) or an increasing failure (deteriorating). A linear plot indicates that there is no observable trend in the failure rate. An increase in the failure rate is depicted by a trend line with a constantly increasing slope, whereas a decrease in the failure rate is illustrated by a trend line with a constantly decreasing slope (Vagenas. N. et al. 1997).

The serial correlation test is a plot of the data pairs (i^{th} TBF, $i-1^{th}$ TBF) for i = 1, …, n, where n is the failure number. If the TBF's are independent, then the points should be scattered randomly on the diagram. If the TBF's are dependant or correlated, the points should lie along a line. It is important to note that the data points should be plotted in the order that they were collected. The points are scattered randomly in a scattered plot throughout. This indicates that the data is free of correlations and can be assumed to be independent. Thus, the assumption of IID can be accepted and consequently the data is fitted to probability distributions for reliability calculations.

The trend test for the present study has been carried out graphically. It is, however, possible to use an analytic method for investigating the trend of the data sets. Before fitting the data, it is important to check whether the data has a trend, i.e., if the rate of failures for the system is increasing, decreasing or constant. One can observe the trend of the failure data by plotting the CTBF and the number of failures. If the trend exists, the line will concave upwards, suggesting an improving system. If the line is concaving downwards, it suggests a system that is deteriorating. If the line is linear, one can be seen that there is no trend in the data.

The objective of the serial correlation tests is to check the relationship between two variables. The scatter plots between the two variables (i^{th} TBF and $(i-1)^{th}$ TBF) exhibits the correlation between the two variables. If the trend and correlation are existed, then the reliability parameters can be calculated by an analytical approach.

2.8.4 Goodness-of-fit (Best-fit) Test

Once the data has been collected and found to be free of correlations and trends, then the next step is to assess the best-fit of a probability distribution model to the TBF or TTR data. Two most commonly used methods for assessing the goodness-of-fit of datasets are the Chi-Squared test and the Kolmogorov-Smirnov (K-S) test (Law. A. M and Kelton. W. D 1991 and ITEM Software, 2007). The Chi-squared test is one of the most widely used tests since it can be applied to discrete or continuous distributions and it is an unbiased test. An unbiased test implies that the test is more likely to reject the hypothesis if it is false. This is a conservative method and reduces the probability that the hypothesis will be rejected if it is true. It is essential to realize that the application of the Chi-squared test to assess goodness-of-fit implies that the observations originate from a normal distribution. Because of the underlying data in most of the reliability studies does not adequately represent the properties of a normal distribution, alternate techniques for assessing the goodness-of-fit are introduced. These techniques are known as non-parametric tests and they are based on a less exact hypothesis than the Chi-Squared test.

One of the most widely used nonparametric tests for assessing the goodness-of-fit is the Kolmogorov-Smirnov (K-S) test (Rao., K. M. and Prasad., P. V. N. 2001). The K-S test examines for differences between theoretical distribution and observed cumulative distribution. This is achieved by determining the largest absolute difference and a random sample of size, n. To determine a maximum acceptable limit of this difference, a level of significance (ε) is applied. The least the value of (ε), the more likely the hypothesis will be accepted. After fitting the distributions parameters need to be estimated. Several methods are available for this, like regression Method, Maximum Likelihood Estimation (MLE) and Bayesian Estimation method, (Samanta, B. et al. 2004).

2.9 RELIABILITY MODELLING TECHNIQUES

The process of understanding the problem or forecasting the life of a component or sub-system before its functioning is called reliability modelling. Reliability modelling techniques are useful to analyse the equipment performance in the industry. International Electro technique Committee (IEC) has developed the reliability modelling techniques based on International standard 300-3-1. The developed reliability modelling techniques are Reliability Prediction (RP), Reliability Block Diagram (RBD). Fault Tree Analysis (FTA), Fault Mode and Effects Analysis (FMEA) and Markov Modelling Analysis (Lendvay. M. 2004).

These reliability modelling techniques are used to predict the component's failure rate and overall reliability of the system. These calculations are also helpful to estimate the design feasibility, to compare the design alternatives, to identify the potential failure modes and to improve the system reliability, etc. Some of the most commonly used reliability modelling techniques are:

- Reliability Block Diagram (RBD)
- Failure Mode Effective Analysis (FMEA)
- Fault Tree Analysis (FTA)
- Markov Modelling Analysis (MKV)

2.9.1 Reliability Prediction

One of the most commonly utilized reliability modelling technique for prediction of failure rate and overall reliability of the system is Reliability Prediction (RP). It can also assist in evaluating the reasons for the occurrence of various potential failure modes. The outcome of the RP analysis can be useful while performing further analyses such as RBD (Reliability Block Diagram), FTA (Fault Tree Analysis) and Failure Mode and Effect Analysis (FMEA). At a specified time, a system or component is either working or it has failed and its operating state varies as time advances. This functioning of the system or component will eventually fail or this failed state will continue until the system is non-repairable. The change of state from working to a breakdown is called failure whereas the change of state from a breakdown to its working is treated as a repair. The repair/maintenance action will bring the system or a component to its working atmosphere with "as good as new" form (ITEM Software, 2007). These conditions are characterized as the meantime to failure (MTTF), the meantime to repair (MTTR) and the mean time between failures (MTBF) (Figure 2.5).

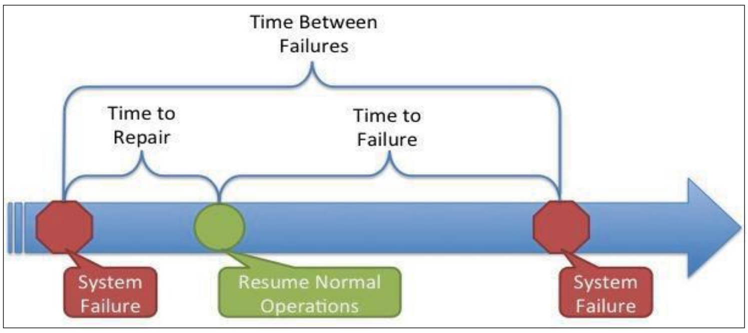


Figure 2.5 One cycle of MTTF, MTTR and MTBF (http://blog.fosketts.net)

MTTF can be computed with the ratio of total working hours to the number of failures in a considered period. This MTTF is typically used in estimating the system reliability for non-repairable systems. MTTR is the ratio of time spent for conducting the CM or PM actions to repair the components. It can also be stated as the expected time duration from breakdown to the completion of maintenance action. This factor is normally used in the estimation of reliability in a repairable system. MTBF time is considered from the first failure to the corresponding successive failure and it can also be taken as a sum of MTTR and MTTF.

2.9.2 Reliability Block Diagram (RBD)

The deductive method called Reliability Block Diagram (RBD) helps to investigate the given system reliability. In RBD analysis, the complex repairable system can be analyzed with graphical representations of logical concepts. In this complex repairable system, each component or sub-system is connected with a systematic configuration. The possible ways of the successful operation of a systems are mainly depending upon the common operational actions of each component/sub-system/part. A wide variety of methods such as series configuration system, parallel configuration system, mixed configuration system and K-out of N system configuration, etc., were readily available to investigate the reliability of a simple or complex system.

In RBD, the blocks of components or sub-systems are arranged in series or parallel configurations that are connected to the output nodes at the extreme sides. The RBD must contain single input and a single output node only. The RBD system is connected by a parallel or series configuration. The redundant nature of the components can be observed in parallel connection and this configuration consists of many paths or links from the initial node to the end node. In series configuration, all the components are joined or linked continuously from the initial node to the end node. An arrangement can contain a series, parallel, or combination of series and parallel connections to make up the RBD (Figure 2.6) (ITEM Software, 2007).

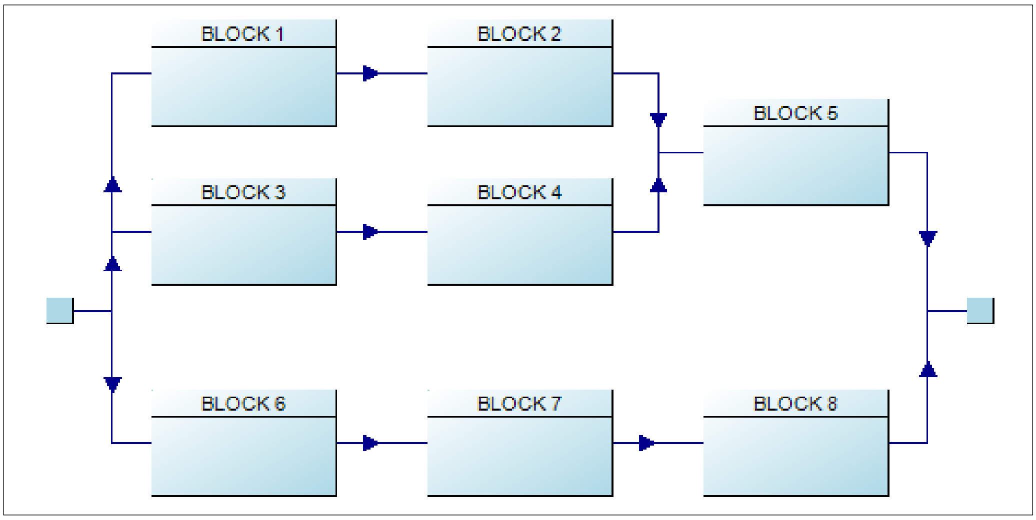


Figure 2.6 An example of RBD

2.9.3 Fault Tree Analysis (FTA)

The Fault Tree Analysis (FTA) is a reliability modelling technique, widely used to measure and quantify the availability of complex electromechanical systems. This technique can also be utilized to identify the most critical parts of the system that can lead to system (top event) failure. In FTA, all the potential failure modes are arranged in a tree-shaped structure. FTA is one of the most commonly used methods for reliability analysis along with Failure Modes and Effects Analysis (FMEA). The FMEA is considered a "bottom-up" analysis, whereas an FTA is considered a "top-down" analysis. This technique evaluates the system/sub-system breakdowns at a time with logical connections. The pictorial representation of the fault tree diagram with all logical events and gates are shown in Figure 2.7.

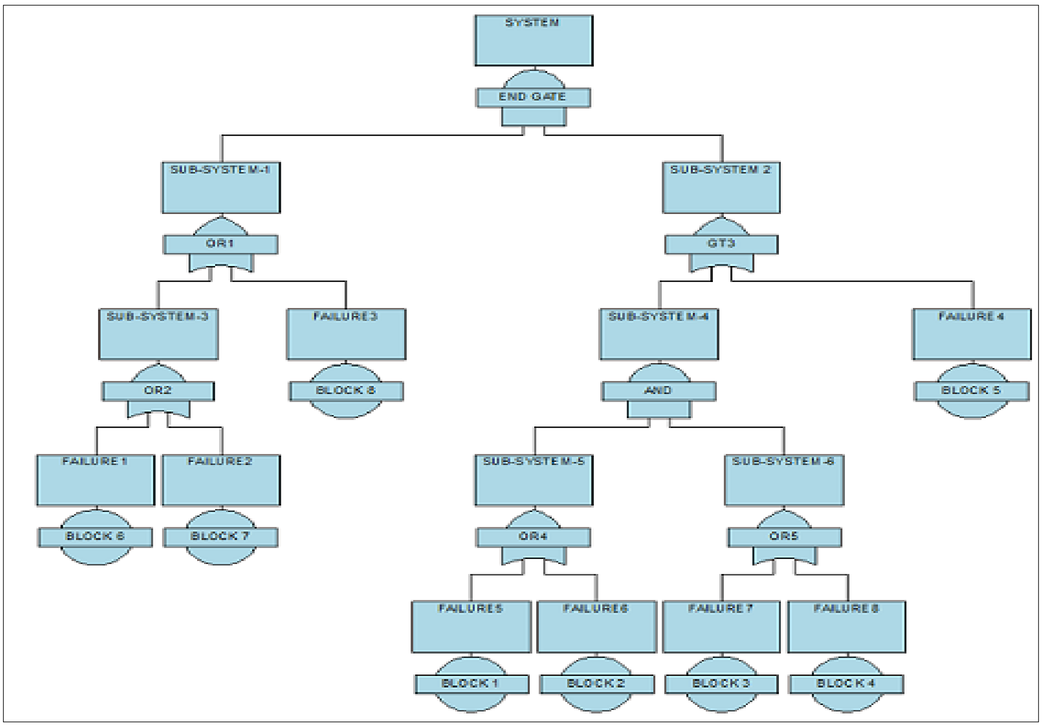


Figure 2.7 An example of FTA

A numerical investigation is performed based on the fault tree. The Boolean algebra methods are used to estimate the usability parameters in a fault-free system/equipment. At each level in the tree, combinations of potential failure modes are portrayed with the logical notations: AND, OR, EVENT. AND gate denotes that an output fault event occurs only if all the input fault events are happening. The probability of failure for the AND gate is determined from the Equation (2.25).

$$P(F) = P(A) \times P(B) \quad (2.25)$$

OR gate denotes that an output fault event occurs if one or more of the input fault events are happening. The failure probability for the OR gate is computed from the Equation (2.26):

$$P(F) = P(A) + P(B) – P(A) \times PB) \quad (2.26)$$

EVENT represents the output/ end gate event that results from the combination of various failure events through the input of a logic gate. FTA relies on experts' process understanding to identify the factors. FTA can be utilized to set up the pathway to the root cause of the fault. FTA is an efficient technique helpful to evaluate how several issues affect the system. The outcome of an FTA contains a visual representation of various breakdown modes. It is also useful for both in risk assessment and in developing the monitoring programs.

2.9.4 Failure Mode and Effect Analysis (FMEA)

Failure Modes and Effects Analysis (FMEA) is a systematic technique of identifying, analyzing and preventing product and process problems before they occur. Its main and highlight activities that eradicate or decrease the probability of the possible breakdown event and document the reports of the advancement. The plan and philosophy of FMEA were first created by the airplane business in the 1960s for the improvement of security and reliability requirements. FMEA was also treated as an efficient way to identify and prevent product and process difficulties before them arising. Preferably this technique should be performed at the stage of product design and development, even though carrying out an FMEA on pre-existing items or procedures may also yield benefits. This helps to reduce the cost of the enrichment of the product and process, as it organizes activities that reduce the possibility of the occurrence of failure (ICH Q9 2006).

Failure Mode Effect Analysis (FMEA) is one of the suitable techniques of reliability modelling used to investigate the failure behavior of a complex system. The FMEA technique is not only used to identify the potential breakdown mode but also used to prioritize the failure modes based on an assessment of risk indexed parameters. In general, prioritization of critical failure can be determined through the calculation of Risk Priority Number (RPN) value. This can be achieved by multiplying the indexes of O, S, and D of each failure. The field failure data of various failure modes are collected from the field investigation. The collected data includes a variety of potential failure modes, reasons for the occurrence of potential failure modes and effects of potential failure modes on the system operation. The group of experts/specialists recommendations can be considered for the predation of the FMEA worksheet. This analyzed worksheet can be used as the historical report for future predictions in the evaluation of the equipment performance. The FMEA worksheet with all requirements of the root cause analysis is given in Figure 2.8. Based on the RPN estimation the critical components can be determined and further suitable recommendations can be suggested to reduce the criticality or system failure.

Row no.	Process name	Process Description	Potential Failure Mode	Potential Effect(s) of Failure	Severity	Potential Cause of Failure	Occurrence	Current Controls Prevention	Current Controls Detection	Detection	RPN	Recommended Action(s)	Action Results			
			Failure description			Description							Sev	Occ	Detec	RPN

Figure 2.8 FMEA datasheet

2.9.5 Markov Modelling Analysis

Another ancient and well-proven stochastic model used to model the randomly changing systems in reliability prediction is a Markov analysis. Markov models are frequently used to model the probabilities of different failure states and the repair rates of a system. It can also be stated as a time-dependent reliability modelling technique, both failure and repair times of the equipment are taken into consideration while estimation of reliability (Hokstad. et al. 2009). Markov analysis is inductive reliability analyzing method, suitable to analyze the functioning of the complex repairable systems and maintenance strategies. Theoretically, it assesses the probability of being in a given functional status of components/sub-assemblies or probability of occurrence of failure/repair events at a given time interval (Lendvay. 2004). The transition diagram of a Markov model is shown in Figure 2.9. In a transition diagram, the circle represents the component states and the arrows represent the transition directions between the states. The amount of failure and repair rates are presented by the arrows with numeric values.

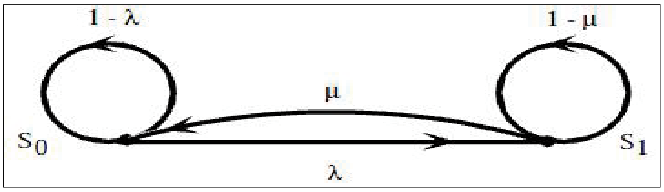


Figure 2.9 Transition diagram of a typical Markov model

Where S_0 is the working state and S_1 the failure/ breakdown state of an equipment. In this analysis, the duration of the time can be considered from state S_0 to state S_1 with a failure rate (λ) and the repair rate (μ) (Samanta, B. et al. 2004) (Ross. S. 1971).

2.10 VALIDATION OF RAM PARAMETERS

The MATLAB based Artificial Neural Network (ANN) and Fuzzy Interface System (FIS) models are the two important approaches for validation of the computed results. The validation helps to acquire the best approximation of the evaluations.

2.10.1 Artificial Neural Network (ANN) Technique

Analytical and statistical approaches will take a bit more time to solve complex problems such as performance estimations as compared with software-based approaches. Nowadays, soft computing techniques catch the attention of researchers for resolving the variety of non-linear challenging issues. In general, most of the conventional analysis approaches cannot be resolved without the utilization of fundamental equations, traditional correlations, or developing distinctive intends from investigational records through trial and error (Harish K. Ghritlahre 2018). Artificial neural network (ANN) technique has been executed in different kinds of difficult issues, which are not comprehended by regular strategy and in different fields. This ANN method cannot take much time to resolve the problems but rather more precisely anticipated because of its adequacy (Harish Kumar N. S. et al. 2018). ANN can model both linear and non-linear systems without considering any kind assumptions (Shakhar. S and Haung. Y 2001). Hence, this tool has been becoming increasingly popular in various Engineering fields.

In the '90s the mining industry has been introduced to several ANN-based systems, some of them finding their way to a fully commercialized product (Kapageridis. I. 1999). Later on universities, and research institutes around the world have started working on a wide variety of research applications (Kapageridis. I. 2002). The application of Soft Computing (SC) techniques in the mining industry is fairly extensive and covers a considerable number of applications (Yama, Lineberry. 1999). The principal SC technologies can be categorized as fuzzy algorithms, neural networks, supporting vector machines, evolutionary communication, machine learning, and probabilistic reasoning Hartman. H and Mutmansky. J 2002, Zadeh. L. A 1994 and McCulloch. W. S and Pitts. W 1943). McCulloch and Pitts (1943) introduced an initial model of an artificial neural network (ANN), which was recognized as the first study of artificial intelligence. Since then, a significant amount of ANN-related research has been conducted (Zadeh. L. A 1993 and Singh. T 2004). The artificial neural network (ANN) has been widely touted as solving many forecasting and maintenance decision modelling problems of machinery (Marzouk. M and Moselhi. O 2002 and Karacan. C. O and Goodman. G. V. 2008). The ANN tool is used to predict the functions of shovel-dumper results using biases and weights of the network to minimize the error between them for interpolation with the computed results (Harish Kumar N. S. et al. 2018). The development of ANN-based methodologies can be used to predict the ventilation emissions from Longwall mines and to develop an expert classification system to identify the type of degasification system for a Longwall operation (Hussan. Al-Chalabi. et al 2014). ANN method helps the decision-makers to determine the best time economically to replace an old machine with a new one; thus, it can be extended to more general applications in the mining industry (Jang. H and Topal. E 2014). The present study is focused on the application of the ANN technique for estimation of the performance of the mining equipment.

Artificial Neural Network (ANN) is a complex information processing system, which is structured from interconnected segmental processing elements, called neurons. These neurons find the input information from other sources and perform generally a non-linear operation on the result and then give final results as output. ANN works in two ways, first learning and then storing the knowledge in interconnects called weights. The basic structure of the ANN is given in Figure 2.10. ANN is a simulation tool in MATLAB that can be used to estimate the values based on input, optimum topology and training processes. In feed-forward networks, each product of input elements and weights are fed to summing junctions and is summed with the bias of neurons is given in Equation (2.27) as follows (Haykin. S 1994 and Ghritlahre. H. K and Prasad.K 2017):

$$= \sum_{i=1}^{n} [\quad] + \tag{2.27}$$

Where, n is the number of input data (i= 0,1,2,3… n) and W_i are the interconnecting weights of the input data , respectively, and is the bias for the neurons. Then this sum X passes through transfer function F which generates (Equation 2.28) an output.

$$(\ ) = \quad = \sum_{i=1}^{n} [\quad] + \qquad (2.28)$$

The most used transfer functions in the hidden layer are TANSIG and LOGSIG. The nonlinear activation function which is widely used is called a SIGMOID function whose output lies in between 0 and 1, and it is given in Equation 2.29 as follows:

$$(\ ) = \frac{1}{1 + \ ^{-}} \qquad (2.29)$$

When at the input or output layer, negative values are found, then the TANSIG transfer function is used, which is written (Equation 2.30) as follows:

$$(\ ) = \frac{1 - \bar{e}^{2}}{1 + e^{2}} \qquad (2.30)$$

The performance index of the different training algorithm is represented by mean square error (*MSE*) and it is formulated as (Equation 2.31):

$$M \quad = \frac{1}{\ } \sum_{i=1}^{n} [\quad - \quad]^{2} \qquad (2.31)$$

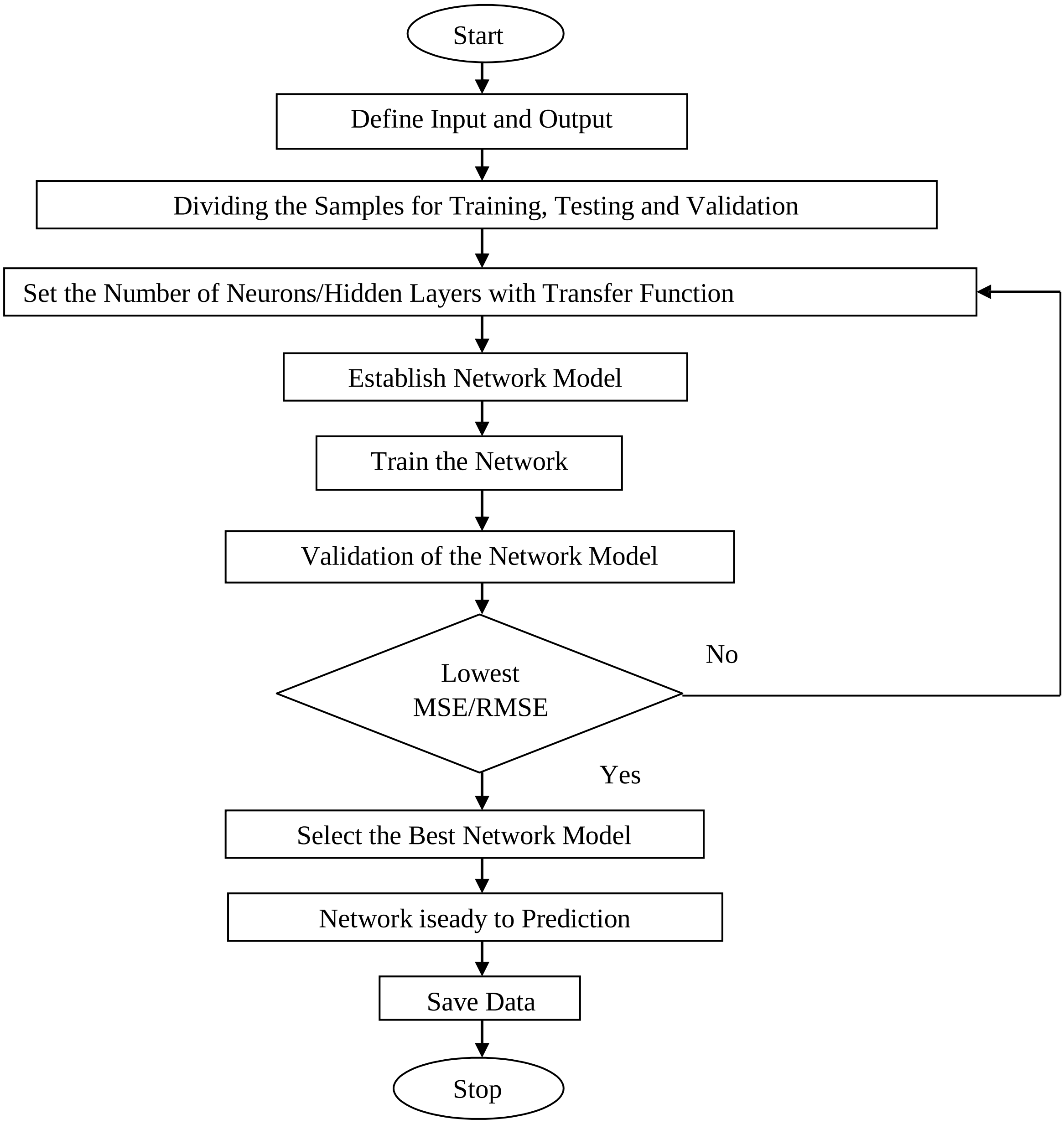


Figure 2.10 ANN simulation flowchart

2.10.2 Fuzzy FMEA

Failure Mode Effect Analysis (FMEA) is an appropriate method for determining design dependability by considering potential reasons for breakdowns and their effects in a complex system. FMEA based risk management analysis can be adopted to prevent undesirable events and to avoid customer dissatisfaction in the industry (Wang. L. X 2008). Industries may have numerous reasons to develop an FMEA report. A good FMEA report can be beneficial by providing, for example, predominant item dependability, fewer structure changes, enhanced quality figure, ceaseless enhancement in an item and process plans, and lower producing costs. The conventional FMEA investigation is typically performed by a specialist in the respective field. The components of FMEA are: recognizing the methods of disappointment and the ensuing issues; surveying the actions which allow flaws occur; evaluating the seriousness of the results of the deficiencies; computing a proportion of the hazard; positioning the shortcomings based on the hazard; checking the viability of the activity, and utilizing an updated proportion of hazard (Ahsen. A.V 2008). While this methodology is straightforward, there are a few weaknesses in getting a decent gauge of disappointment evaluations. To remedy this, another hazard evaluation framework dependent on the fuzzy set hypothesis and fuzzy principle base hypothesis is proposed. According to Balaraju Jakkula. et al. (2019), FMEA is one of the suitable techniques of reliability modelling used to investigate the failure behaviour of a complex system. In conventional FMEA, the risk level of failures, a ranking of failures and prioritization of necessary actions are made based on estimate risk Priority Number (RPN). While this approach is easy and uncomplicated, there are a few flaws in acquiring the best approximation of the failure. The estimation of RPN is made by multiplying the Severity (S), Occurrence (O) and Detection (D) alone and irrespective of the degree of importance of each input. Hence, a new risk management approach known as the Fuzzy rule base interface system was proposed to mitigate the failures. Fuzzy FMEA is designed to acquire the highest Fuzzy RPN value which will be used as the focus of enhancements to reduce the probability of occurrence of some kind of failure for a second time.

Fuzzy set theory is a way to deal with exchanging the vulnerability of hypothetical relations into numerical systems. By a pattern has been developing in FMEA writing which utilizes fuzzy linguistic terms for depicting the three hazard factors S, O, and D. Many of these researchers assumed that Fuzzy FMEA approach is the great foundation for obtaining accurate responses (Gargama, H and Chaturvedi. S. K 2011 and Keskin. G. A. and Özkan. C 2009). The vast majority of the current investigations into fuzzy FMEA writing by utilizing 'If-Then' rules. This paper portrays the exact and sensible positioning of the needs of different disappointment modes by the usage of regular FMEA and proposed Fuzzy FMEA approaches. There are important efforts have been prepared in FMEA to conquer the inadequacy of the conventional RPN (Wang 2008). Particularly fuzzy modelling with fuzzy If-then rule base, have been recommended to conquer the disadvantages. In the investigation of Fuzzy based FMEA model, a specialist can describe the risk indexed factors (S, O and D) using a fuzzy linguistic path (Bowles. J. B and Pelaez. C. E 1995 and Chin. K. S et al. 2008).

According to Zadeh , L. A and Desoer, C. A (1965), the fuzzy methodology is a significant theory which deals with the failure information. The factors such as Severity (S), Occurrence (O) and Detection (D) which are used in FMEA are fuzzified using suitable membership functions. The Fuzzy system is a knowledge-based system that is constructed from proficiency and knowledge in the form of fuzzy IF-THEN rules (Tay. K. M and Lim. C. P 2006). While constructing a knowledge-based model, expert familiarity and decision can be utilized to make the FMEA evaluation technique more sensible and suitable. The fuzzy conclusion is then de-fuzzified to acquire RPN value. The concepts of Fuzzification, Fuzzy rule base, De-fuzzification are given in Figure 2.10.

Fuzzification: Fuzzification is a process to transform the hard inputs into membership degree quantities which expresses how well the input is in the right places to the linguistically defined terms (Rajiv. Kumar. Sharma et al. 2005). Specialist decision and knowledge can be utilized to describe the degree of membership function for a particular variable. Along with Fuzzification, a fuzzy logic controller acquires input information, likewise called the fuzzy variable, and examines it as indicated by client characterized diagrams called membership functions.

Fuzzy rule base: Fuzzy rule base explains the level of criticality of a system for each combination of input variables. Regularly articulated in ‘If-Then', they are created in linguistic terms using two approaches (i) Proficiency of a specialist (ii) Process of the Fuzzy based model (Zimmermann. H. 1996). Expert's judgment and experience can be used to define the degree of membership function for a particular variable.

De-fuzzification: De-fuzzification is a technique to look at the standard results after they have been normally included and afterward compute the value that will be the last yield of the fuzzy controller. During de-fuzzification, the controller exchanges the fluffy yield into genuine information esteem (Rajiv. Kumar. Sharma et al. 2005).

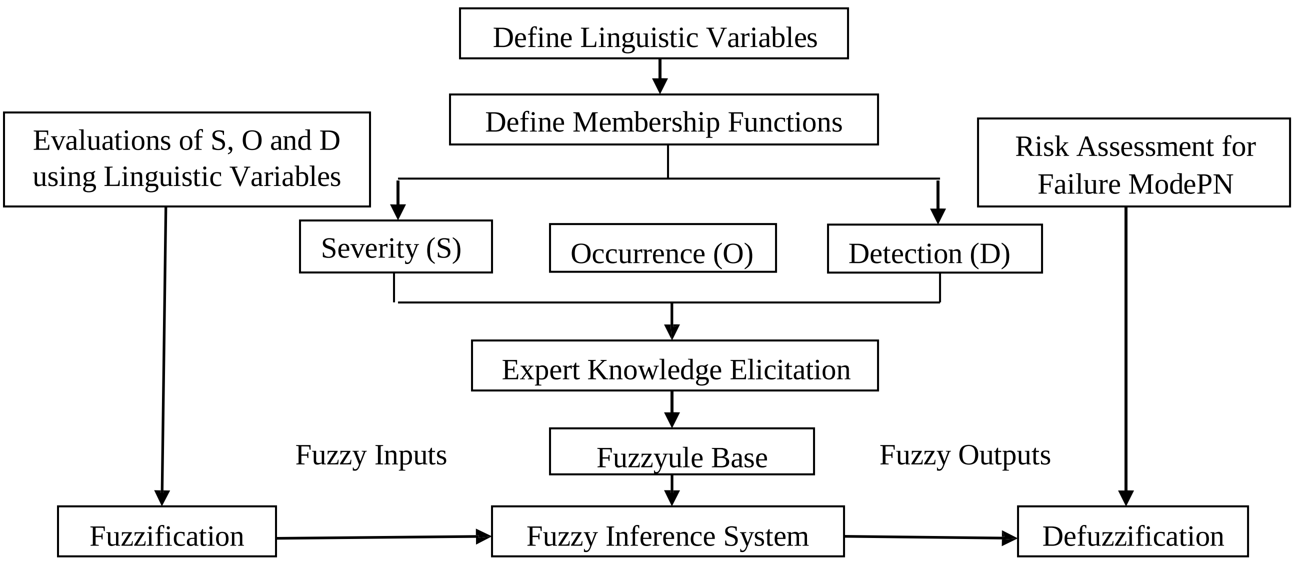


Figure 2.11 Fuzzy FMEA flowchart

2.11 OVERALL EQUIPMENT EFFECTIVENESS (OEE)

Overall Equipment Effectiveness (OEE) is a tool used to identify and categorize the major causes or reasons for poor performance. It is used to measure the equipment performance by considering various parameters like overall time, speed, and output, or production. OEE provides the platform for setting improvement priorities and sets of foot cause analysis. OEE is expressed in percentage and is used to track the trend of improvement or decline of the equipment's effectiveness over some time (Johnson. H. T and Lesshammar. M 1999).

OEE is a universally accepted method for measuring the improvement potential of a production process with one simple number (OEE 2012). OEE is also referred to as Overall Equipment Efficiency (Impact. O. 2012) but for this research, it is considered as Overall Equipment “Effectiveness”. OEE is a major Key Performance Indicator (KPI) (ATS International. B. V. 2010) and an important metric for many companies initiatives in operational excellence (INS research 2012). The OEE is used as a tool is to quantify the machine efficiency or effectiveness (Dhillon. B. S 2008). It considers the most common and important sources of productivity losses, as shown in Table 2.4. The losses are quantified by compensating the availability, performance and quality measures to estimate OEE.

Table 2.4 Six big losses of various factors (Sivaselvam. E and Gajendran. S 2014)

Major event category	**OEE Parameter**	**Type of loss**	**Typical example**
Machine breakdowns	Availability	Downtime	Equipment failures, Tooling damage, Unplanned maintenance
Machine adjustments/setups	Availability	Downtime	Process warm-up, Machine change over’s, material shortage
Machine stops	Performance	Speed	Product misdeeds, component jam, product flow stoppage
Machine reduced speeds	Performance	Speed	Level of machine operator training, Equipment age, Tool wear
Machine bad parts	Quality	Quality	Tolerance adjustments, worm up process, damage,
Machine production bad parts	Quality	quality	Assembled incorrectly, rejects, rework

Total Productive Maintenance (TPM) aims to maximize equipment effectiveness. It consists of a range of methods that are known from maintenance management experience to be effective in improving reliability, quality and production. The Original goal of total productive management is to "Continuously improve all operational conditions, within a production system; by stimulating the daily awareness of all employees" (Nakajima. S 1988). A metric termed the "Overall equipment effectiveness (OEE)" is the benchmark used for world-class maintenance programs. The OEE is established by measuring equipment performance. Measuring equipment effectiveness must go beyond just availability or machine uptime. It must factor in all issues related to equipment performance.

During the 1980s, Total Productive Maintenance (TPM) has become known in manufacturing industries and OEE was proposed by Nakajima. S (1988) deals with equipment/machinery to evaluate the progress of TPM. It is interpreted as the multiplication of availability, performance and quality. Overall equipment effectiveness (OEE) is a widely used quantitative metric in manufactory systems for controlling and monitoring the productivity of production equipment, and also as an indicator and driver of process and performance improvements (Bulent. D et al. 2000). OEE is a key performance measure in the production industry, with three important factors which are availability, productivity and quality. This metric has become widely accepted as a quantitative tool essential for the measurement of productivity in manufacturing operations (Zemestani. G 2011).

2.11.1 OEE Calculation

To calculate or measure the performance of underground mine equipment, OEE should be taken as an indicator or metric. However, OEE significance for machinists will be very fewer unless these influencing parameters are deliberated and evaluated more effectively than the regular measures (Paraszczak. J. 2005). OEE percentage can be calculated from the following Equation 2.32 (Moubray. J. M. 1997):

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality} \qquad (2.32)$$

The value of OEE is calculated in two different ways. One is production-related which deals with produced output for the anticipated targets. The alternative approach is time-related, wherein, data related to working hours, breakdown hours, etc. is collected and utilized for evaluation of OEE. From the basic information or collected data, such as shift schedule hours, maintenance hours, breakdown hours, idle hours, etc, the availability and utilization percentages, production index rate and overall equipment effectiveness can be determined. These factors and indices have been defined and their importance brought out from the following relations (Yunos. Bin. Ngadiman, bin. Ngadiman et al. 2013).

2.11.2 Benchmarking World-Class OEE

As mentioned in the literature before, Nakajima. S. (1988b), the founder of OEE had also set a world-class OEE score for the users to benchmark. The world-class OEE is set at a minimum score of 90 percent for availability rate, 95 percent for performance rate, and 99 percent for quality. Multiplying these factors together obtained a minimum score of 85 percent world-class OEE rate. In this present study, the computed OEE values of machinery were validated with world-class OEE values to identify the present status of the equipment.

2.12 DESCRIPTION OF EQUIPMENT

An underground mining operation consists of several categories of operation as shown in Figure 2.12. The focus of this thesis is the second part of the operation where the ore and minerals are loaded from the face by LHD machines and normally dumped into ore passes.

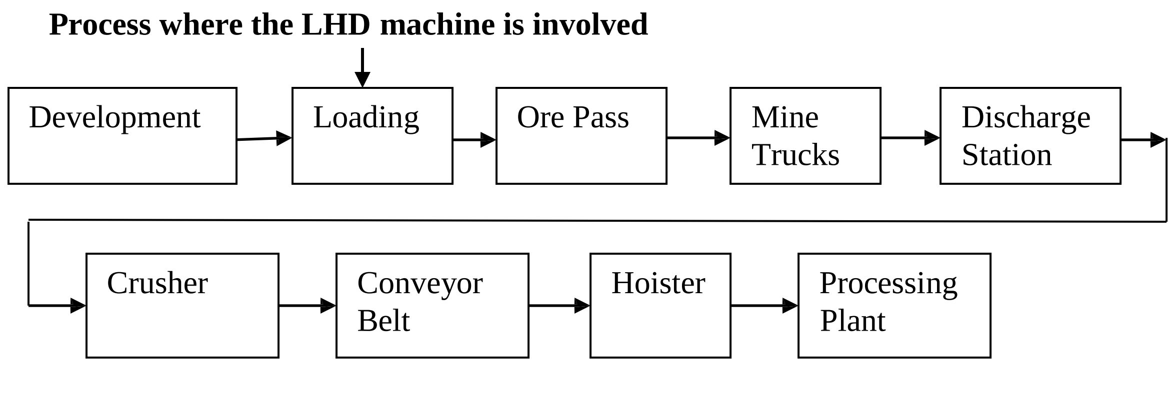


Figure 2.12 Flowchart from loading to processing plant (Gustafson. A et al. 2013)

LHDs are used in most of the underground mines for loading, transportation and dumping of ore and minerals. LHD is a self-propelled machine with an integral front-mounted bucket with a supporting structure and linkage which loads or excavates through forward motion of the machine, and lifts, transports and discharges material. These vehicles are started to be used first in the 1950s and are widely spread by the 1960s. Today, they are employed in most of the underground coal and metal mines all over the world, (Nick. Vayenas and Sihong, Peng. 2014). There are several operating modes available for LHDs e.g. manual operation, line of sight remote operation, tele-remote operation, automatic operation and semi-automatic operation. Today, manual operation is the most common way of moving ore; however, automatic LHD machines are also planning to be used for productivity improvement. The advantages of automation includes process consistency and ability to counter the labor shortages (Chadwick. J. 1996). Manually operated LHDs are shown in Figure 2.13 (a) and (b).

Figure 2.13 (a): Manually operated LHD, (b) LHD at the operating environment

Each LHD machine consists of two parts connected by an articulation point which gives them a high level of ability to move in narrow mine drifts (Dragt. B. J et al. 2005). Each section of the unit has a set of non-steerable rubber wheels. The back of the machine contains the engine, and the front contains the bucket. The bucket, the steering, and the brakes are hydraulically operated. Several operating modes and combinations are available for LHD machines: manual operation, line of sight remote operation, tele-remote operation, semi-automatic operation and automatic operation. There are advantages and disadvantages to each operating mode, and selecting the optimal one is not straightforward. Since the machines are operating in a harsh environment, several issues affect the decision. Besides the machine and personnel-related issues, there are mining-related issues such as fragmentation, oversized boulders, road conditions, ventilation, etc. that must be considered.

The importance of high reliability is accentuated in all underground mobile mining equipment operations (Kumar. U. et al. 1989 and Hoseini. S. H. et al. 2012). More failures can be expected if a component or system has poor reliability (Kumar. U. 1990 and Hoseini et al. 2012). Kumar. U (1990) has noted that the failure characteristics of the equipment are influenced by the designed reliability. All failures have a cause and an effect; thus, after being identified, flaws can either be designed out or accommodated, thereby increasing the maintainability (Kumar. U. 1990). The purpose of this research work is to investigate the performance of LHD machines as well as to recommend the necessary managerial actions for performance improvement characteristics.

In this chapter literature review has given for the addressed objectives in the thesis with relevant concepts, theories, and practical studies of past historical scientific studies. The corresponding chapter provides brief information on field investigations for the collection of failure data of LHD machines. It also briefly discusses research methodology, data collection processes, classification and analysis. The required data pertains to field investigations of three underground coal and non-coal mines of India.

CHAPTER 3

FIELD INVESTIGATION AND DATA COLLECTION

3.1 STUDY AREA-1

3.1.1 Description of the Mine

The field investigation was carried out in one of the underground metal mines of the northwest part of India known as M/s Hindustan Zinc Limited (HZL), Vedanta Group. Mine-A belonging to HZL is India's one of the largest underground mine with the production of 4.5 Mt in the year 2018. With an average reserve grade of 7%, the mine differentiates itself with its silver-rich, zinc-lead deposit and highly mechanized and low cost of operations.

Mine-A of HZL is located about 6 km away from the Rajpura Dariba Mines of Rajsamand District in Rajasthan. Mine-A is operating as an underground mine for the production of lead and zinc ore. The mine was opened in the year 1999 and started production in 2006. The current annual production is 2.0 Mt per annum and the treatment of ore is 4.25 Mt per annum in the FY 2018-19. Mine is having 6 openings with 2 ramps, 4 ventilation raises and an incline. North ramp and South ramp (5.5m x 5.0m, 1 in 8 gradients) are suitable for deploying 50t capacity mine trucks and 17t capacity LHDs. In the North and South, each ventilation raise is equipped with a 200m^3/sec main exhaust fan. Currently the mine is being worked out by levels with RLs 425, 400, 375, 350, 315, 300, 290, 265, 240, 215, 195,160, 130, 100 and 65m. Mine-A is operating as an underground mine with a production capacity of 2.0 Mtpa and the mine was divided into 3 blocks i.e. Upper block (400-315mRL), Middle block (290-215mRL) and Lower block (195-160mRL). Stopes in the upper block is mined out completely and are utilized the voids created for dumping waste.

The mining method used for current mine is the blast hole open stopping with filling. The ore is crushed at the surface and transported to the beneficiation plant for further crushing; milling; and flotation processes. LHDs are used as the main workhorse for ore handling and transportation. LHDs are used to scoop the extracted ore, with a bucket, load it into the bucket, and dump it in the bottom of the mine to undergo a primary crushing operation before being hoisted to the surface out of the mine. Currently, the mine is operating with 10 numbers of LHDs with a capacity of 17 m^3 manufactured by M/s Sandvick Company Limited. The Sandvik LH517 model is a high-capacity, 17-metric-ton LHD designed to deliver the projected levels of production and productivity. A three-pass loading of Sandvik LH517 underground LHD optimizes the ore-moving process. LH517 model LHD machine at a workshop for maintenance/repair action is shown in Figure 3.1 (a) and (b). The technical specifications of the machine are given in Table 3.1. The time length of the Mine-A operation is given in Table 3.2.

Figure 3.1 (a) and (b) LH517 model LHD machine at a workshop for maintenance

Table 3.1 The technical specification of Sandvick-517 model LHD machine

Diesel engine	Volvo TAD1341VE, Tier 2
Output	275 kW (369 hp) @ 2 100 rpm
Torque	1 905 Nm @ 1 260 rpm
Number of cylinders	In-line 6
Displacement	12,78 l
Cooling system	Liquid-cooled
Combustion Principle	4-stroke, direct injection, turbo with intercooler
Air filtration	Donaldson Power Core
Electric system	24 V starter and accessories
Exhaust system	Catalytic purifier and muffler, double-wall exhaust pipe
Average Fuel	35,0 l/h (at 50% load)
Consumption: Fuel Tank Capacity	485 l (128 gals)
Converter	Dana C9602: No lock-up
Transmission	Power shift transmission with modulation, four gears forward and reverse, automatic gear shift control
Axle: Front Axle	Kessler D106, Posi Stop brakes, limited-slip differential, fixed
Rare Axle	Kessler D106, Posi Stop brakes, limited-slip differential oscillating
Tire size	29,5x29 L5S, 34 ply
Vehicle Weights: Total operating weight	44 030 kg
Front axle	18 270 kg
Rear axle	25 760 kg
Total loaded weight	61 200 kg
Front axle	45 070 kg
Rear axle	16 130 kg
Capacities: Tramming capacity	17 200 kg
Break out force, lift	35 000 kg
Break out force, tilt	29 450 kg
Tipping load	35 500 kg
Standard bucket	7.0 m^3
Main Dimensions Total length	11 120 mm
Maximum width	3 000 mm
Height with canopy / cabin	2 754 mm
Bucket Motion Timings: Raising time	8.3 sec
Lowering time	4.3 sec
Speed:1st Gear	5.9 km/h
2nd Gear	10.7 km/h
3rd Gear	18.8 km/h
4th Gear	33.9 km/h

Table 3.2 Time length of the Mine-A operation

Sl.No	**Description**	**Time**
1	Number of Scheduled days/year	365 days
2	Number of working days/month	30
3	Number of shifts/day	3 No/.
4	Number of Hours/Shift	8 hours
5	Daily Maintenance Hours/Shift	2 hours
6	Effective Working Hours/Shift	6 hours
7	Effective Working Hours/day	18 hours
8	Effective Working Hours/month	468 hours
9	Effective Working Hours/year	5,616 hours

3.2 STUDY AREA-2

3.2.1 Description of the Mine

The second field investigation was carried out in one of the underground metal mines (Mine-B) of the southern part of India, belonging to M/s Hutti Gold Mines Company Limited (HGML). The Hutti gold mine is located at the north-western part of the Hutti-maski greenstone belt in Raichur district, Karnataka state. The mine is currently being operated through three shafts namely Mallapa shaft – 899.20m(vertical), Central shaft – 871.86m(vertical) and Village shaft – 552.86m(inclined). HGML's production has steadily increased over the years. Over the years, the company has implemented several technology updating schemes in mining and processing leading to an increase in the competitiveness of equipment operation. The use of bulk mining methods viz. Large Dia Blast Hole (LDBH) stoping and sub-level mining have achieved higher levels of safety and productivity. The cut and fill method is not being used nowadays as it is the most time-consuming method. The various types of mining methods followed in Hutti Gold mines are, Cut and fill method, LDBH, and Sublevel & LDBH (combined) method of extraction. In this mine generally sub-level stoping combined with large diameter blast whole method is used. The ore blocks are blasted in LDBH fashion and the levels are divided into intermediate levels called sub-levels where the charging and blasting operations are carried out.

The ore that is broken from the reef is then loaded into the locos and they dump it into the transport chute available at every level from where the material flows down to the 20^{th} level. On that level, the ore is loaded into bandies and from there they are transported to the bottom where huge rock breakers are installed. After blasting, the materials pile up and the mucking operation is done using hopper loader which directly unloads it into the chutes. Currently, the mine is operating with 5 numbers of LHDs having a bucket capacity of 3 m^3 made by M/s Emico Elicon and M/s Sandvick Company Limited. The technical specifications of the LHD-811 machine are given in Table 3.3. The time length of the HGML operation is given in Table 3.4.

Table 3.3 The technical specifications of M/s Emico Elicon-811 LHD

Electric Motor	50 HP, 550 V 3 Ph, 50 Hz, 1470 RPM
Transmission	CLARK Transmission 20000 Series with industrial Torque Converter
Bucket Pay Load	2270 Kg
Bucket Breakout Force	3629 Kg
Bucket Capacity	1.50 Cu.M Heaped/1.2 T/1500 Kgs. Of water
Machine Weight	7.10 T Approx.
Machine Total Height	1950 – 2000 mm
Machine Width	1475 mm
Machine Length	5855 mm
Inner	1876 mm
Outer	5855 mm
Speed 1st Gear	2.70KMPH
2nd Gear	5.10 KMPH
3rd Gear	9.20 KMPH
Transmission Charging Pump	Gear Type 70 LPM
Hydraulic Pump	Tandem Gear Type Pump (2 Deliveries 16.00 GPM Max Pressure 2700 PSI, 14.50 GPM Max Pressure 2200 PSI)
1st Delivery 16 GPM	Service Brakes, Steering and Bucket Operations
2nd Delivery	Cable Reeling, Parking Brakes and Radiator
Negotiable Gradient	1 in 6 inline 1 in 8 in Lateral
Articulation Angle	22.5 Deg.
Tyres	11 X 20 Tube Type Pressure 90 PSI
Oscillation	Bolster (+/-) 8 Deg.
Cable Reeling	Random 80 mtrs.

Table 3.4 Time length of HGML mine operation

Sl.No	Description	HGML
1	Number of Scheduled days/year	365 days
2	Number of working days/month	30
3	Number of shifts/day	3 No/.
4	Number of Hours/Shift	8 hours
5	Daily Maintenance Hours/Shift	2.5 hours
6	Effective Working Hours/Shift	5.5 hours
7	Effective Working Hours/day	16.5 hours
8	Effective Working Hours/month	429 hours
9	Effective Working Hours/year	5,148 hours

3.3 STUDY AREA-3

3.3.1 Description of the Mine

Different technologies like mechanized Longwall, Blasting gallery method and intermediate mechanization (LHDs) have been successfully adopted in various UG mines of M/s The Singareni Collieries Company Limited (SCCL). The underground mines of SCCL have been extensively developed by conventional Board and Pillar workings where the gradient of the coal seams vary between 1 in 2.5 to 1 in 10. The SCCL had introduced suitable mechanization in mines wherever conditions favour for extraction of developed pillars. The field investigations in respect of coal mines were carried out in one of the underground mines (Mine-C) of the SCCL, Ramagundam (RG-I) area-1 in Karimnagar District, Telangana State. The SCCL is operating 51 underground mines and 9 opencast mines. Mine-C is in RG-I area of SCCL and is located in the central part of Ramagundam coal belt of Godavari Valley Coalfield.

The SCCL increased its underground production by introducing appropriate mechanization and technology such as LHD, SDL and Continuous miner in some underground mines for both development and depillaring operations. The colliery (Mine-C) is being operated in seam 4 and 6 by board and pillar method and coal extraction is done by drilling and blasting operations. The LHDs are used for loading and transporting of coal in underground mines. LHDs are used to scoop the blasted coal into the bucket, move with the loaded bucket and unload on to a nearby belt conveyor from where coal is transported outbye of the district and finally to surface through existing transport network. Currently, the mine is operating with 5 numbers of LHDs having a bucket capacity of 3 m^3 made by M/s The Emico Elicon Company Limited. The technical specifications of 912 E model LHD are given in Table 3.5. The time length of the mine operation is given in Table 3.6.

Table 3.5 Technical specifications of 912 E model LHD machine

Electric Motor	100 HP, 550 V 3 Ph., 50 Hz, 1470PM
Transmission	Transmission MHR 32,000 Series with 13.7 Torque Converter
Bucket Pay Load	4000 Kgs.
Bucket Breakout Force	6700 Kgs (Tilt) 11890 Kgs. (Combined)
Axle	Heavy-duty, No spin type, all immersed breaks.
Bucket Capacity	3 m^3
Machine Weight	12500 Kgs
Machine Total Height	2.1 m
Machine Width	1.9 m
Machine Length	7.85 m
Dumping Time	4 s
Lifting Time	4 s
Lowering Time	3 s
Maximum Dumping Height	2.7 m
Negotiable Gradient	1 in 4 - inline 1 in 5 – Gradient with safety precaution
Articulation Angle	22.5 Deg.
Transmission Charging Pump	Gear Type 70 Lumped Parameter Model (LPM)
Hydraulic Pump	Gear Type
Tyres	14.00 X 25 (Tube Type) 120 Pounds per Sq. Inch (PSI)
Oscillation	Bolster (+/-) 8 Deg.
Radiator – Fan	The belt is driven by Electric motor at 2200pm
Total no. of Hydraulic pumps	Gear type pump 01 No’s
Total No. of hydraulic motors	Cable reeling motor 01 Nos.
Cable reeling	Random 120 meter
Lighting voltage	24 V AC
Pilot voltage	12 V rectified with a half-wave rectifier

Table 3.6 Time length of the mine

Sl.No	Description	SCCL
1	Number of Scheduled days/year	365 days
2	Number of working days/month	30
3	Number of shifts/day	3 No/.
4	Number of Hours/Shift	8 hours
5	Daily Maintenance Hours/Shift	1 hour
6	Effective Working Hours/Shift	7 hours
7	Effective Working Hours/day	21 hours
8	Effective Working Hours/month	546 hours
9	Effective Working Hours/year	6,552 hours

3.4 RESEARCH METHODOLOGY

The methodology proposed to achieve the research objectives is as follows:

1. Field investigations were carried out in three different study areas for data collection. The required data were collected from the records maintained by maintenance personnel and fleet manager in the form of handwritten spreadsheets, computerized soft copies and real-time monitoring for 2 years. This includes both breakdown and repair data of various failure modes of LHDs to identify the 'influencing parameters' on equipment performance.

- *Study area 1:* An underground metal mine belonging to M/s The Hindustan Zinc Limited (HZL), Vedanta Group, Rajpura Dharibha in Udaipur district, Rajasthan state, India.
- *Study area 2:* An underground metal mine belonging to M/s The Hutti Gold Mines Company Limited (HGML) in Raichur district of Karnataka state, India.
- *Study area 3:* An underground coal mine belonging to M/s The Singareni Coal Collieries Company Limited (SCCL), Ramagundam (RG)-1 area, Karimnagar district, Telangana state, India.

2. The LHD machine is classified into several sub-systems to categorize the different varieties of failure modes.

3. Key performance indicators (KPIs) such as percentage availability and capacity utilization of LHDs were calculated based on the collected data during field visits.

4. Before the assessment of operating characteristics and failure patterns of a machine, trend and serial correlation tests were performed to validate the Independent and Identical Distribution (IID) nature of the data sets.

5. Null-hypothesis of the datasets of LHDs were tested for identification IID nature using the Chi-squared (Statistic U) test.

6. The best-fit (Goodness-of-fit) distribution of datasets was estimated by plotting the cumulative probability plots using the Kolmogorov-Smirnov (K-S) test, Maximum

Likelihood (ML) test with consideration of Exponential, Weibull-1 parameter, Weibull-2 parameter, and Weibull-3 parameter functions.

7. The percentage of reliability of each sub-system was calculated from the Cumulative Distribution Function (CDF) plots in 'Isograph Reliability Workbench 13.0 (IRW)' and the percentage of maintainability and availability were estimated from the results of Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR) and Maximum Likelihood Estimation (MLE) parameters.

8. Reliability-based Preventive Maintenance (PM) time intervals were computed to forecast system reliability. Overall system reliability (ORs) of each LHD was estimated from the RBD calculation. Further, Remaining Useful Life (RUL) of the equipment was also estimated to identify the threshold value of the LHDs.

9. Failure behaviour of the system and percentage contribution of each component on the system failure was determined using FTA and FMEA reliability modelling approaches. Validation of the computed results of Isograph Reliability Workbench (IRW) was made with the 'MATLAB' based ANN and Fuzzy interface system predicted values.

10. Overall Equipment Effectiveness (OEE) of LHDs have been estimated with results of availability, percentage rate and quality rate and compared with world-class standards. The Steps involved in research methodology are given in the flowchart (Figure 3.2):

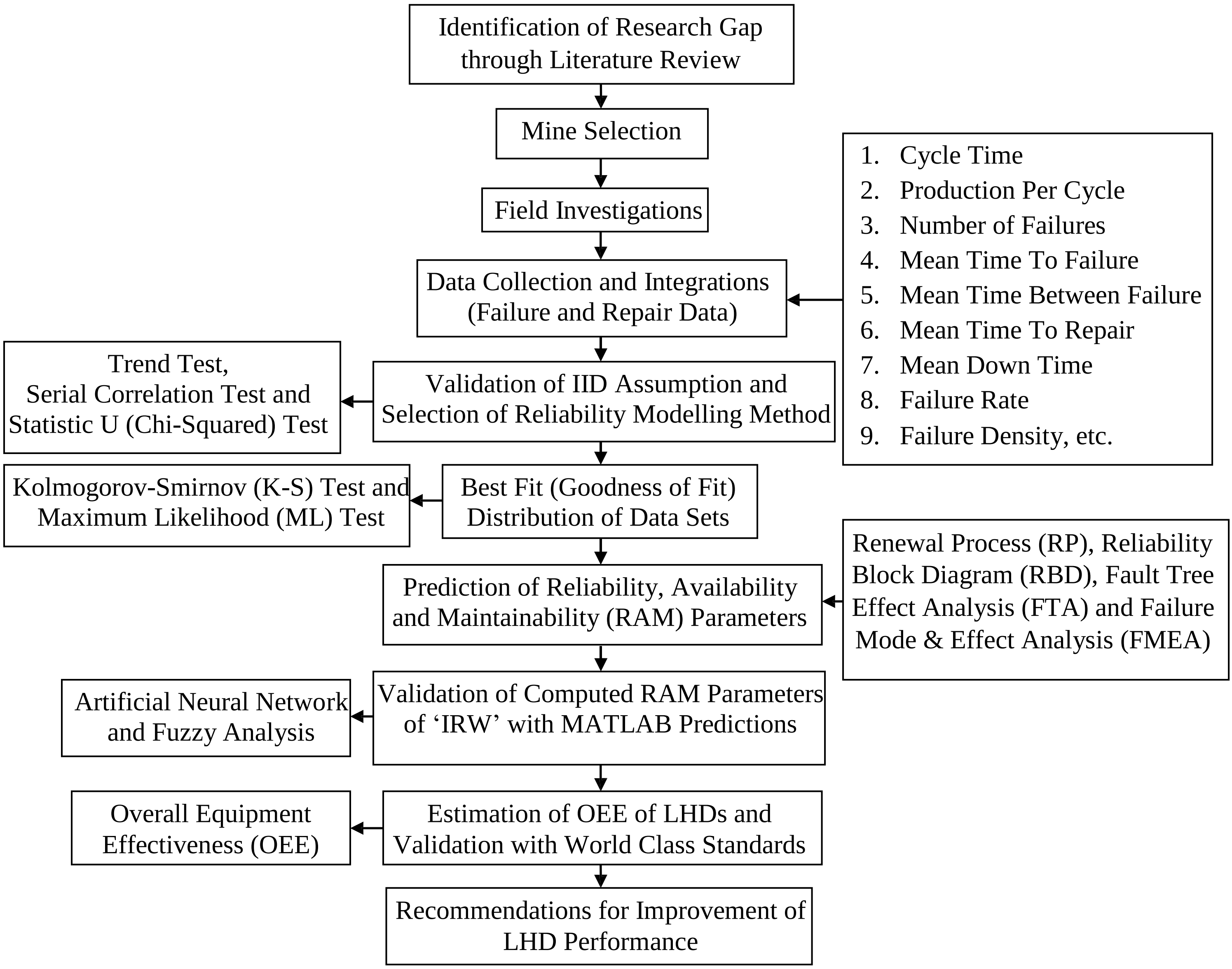


Figure 3.2 Research methodology flow chart

3.5 DATA COLLECTION

3.5.1 Classification of System and Sub-system

Before the collection of field failure data of LHDs, it is necessary to identify the type of failure mode causing the system to be inoperable to fail. The breakdown of the equipment is caused due to several reasons that may be attributed to component failure; inadequate maintenance; wrong operation, etc. To recognize the type of failure, the equipment should be classified into several sub-systems. The classification of these was made based on maintenance/repair records of the maintenance crew and fleet managers (Vagenas, N et al., 1997). From the field investigation in study area-1, 10 LHDs are considered for detailed study. In this classification, each LHD was treated as an independent system and are named as LH21, LH22, LH24, LH25, LH26, LH27, LH28, LH29, LH30 and LH31. Similarly, in study area-2, 5 of LHDs (namely LHD-1, LHD-2, LHD-3, LHD-4 and LHD-5) are the focus of the investigation. Likewise, in study area-3, 5 LHDs (namely E1-LHD1, E2-LHD2, E3-LHD3, E5-LHD5 and E6-LHD6) were selected for the performance analysis. Sub-systems of LHDs were classified into seven numbers (Table 3.7) such as sub-systems of the engine (SSE), braking (SSBr), tyre (SSTy), hydraulic system (SSH), electrical system (SSEl), transmission system (SSTr) and mechanical system (SSM).

Table 3.7 Sub-system classification of LHD

Sl. No	Sub-System	Failure Mode	Code
1	Engine	Radiator, piston-cylinder, ‘O’ ring failure, etc.	SSE
2	Braking System	Oil leakage, brake jamming, brake pedal problem, etc.	SSBr
3	Tyre/Wheel	Tyre puncture, hose (wearing) failure, misalignments.	SSTy
4	Hydraulic System	Leakages, lubrication, cylinder, hoses, pumps, suspension systems, etc.	SSH
5	Electrical System	Charging, wiring, gauges, starter, cable reel, socket, signal light, sensor problem, etc.	SSEl
6	Transmission	Drivelines, torque converter, gear train wear out, etc.	SSTr
7	Mechanical System	Chassis damage, differential, front &rear axle frame, cabin, bucket/boom wear out, welding problems, etc.	SSM

3.5.2 Collection of Breakdown and Repair Data

After the system and sub-system classification, the very first step in the operational methodology is the collection of required data from field investigations. The required data were collected from day to day reports of downtime, and maintenance/repair time recorded in spreadsheets, and enter the data in the computer. The collected information includes breakdown hours (BDhr), shift scheduled hours (SShr), scheduled maintenance hours (SMhr), idle hours (IDhr) and several downtimes, etc. The data of each system was recorded separately from three different study areas quantitatively for two financial years. Idle time of the machine caused by different influencing factors for 2 years is given in Table 3.8. The Breakdown and idle time for 2 years of each system were collected and illustrated in Table 3.9, Table 3.10 (a), and (b), and Table 3.11 (a) and (b).

Table 3.8 Downtime (Idle time) classification of LHD

Sl. No	Reason/Cause for Machine being Idle	Down time code
1	Accumulator Problem	DAC
2	Machine Shifting	DSH
3	Anchorage Shifting	DAN
4	Shift Change	DSC
5	Shortage of Coal	DBL
6	Roof Support	DRS
7	Bad roof	DBR
8	Drilling and Blasting	DDB
9	Strike and tool down	DST
10	Conveyor belt problem	DBP
11	Shortage of manpower, drum and body cable jam	DOT

Table 3.9 Collected field failure data of LHDs of study area-1 (in hours)

Equipment	SShr	BDhr	SMhr	IDhr	No. of Downtimes (No/.)
LH21	17544	2180	167	2873	167
LH22	17544	1716	417	400	221
LH24	17544	2308	273	948	205
LH25	17544	1755	526	151	176
LH26	17544	1931	340	551	176
LH27	17544	1582	391	233	144
LH28	17544	1685	467	190	196
LH29	17544	1293	308	344	164
LH30	17544	942	219	766	84
LH31	17544	897	468	686	124

Table 3.10 (a) Breakdown Hours (BDhr) data of LHDs of study area-2 (in hours)

Machine	SShr	SMhr	Breakdown Hours							Total BDhr
			SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM	
LHD-1	17856	398.5	50.5	34	112	68.5	144.5	40.5	127	660.5
LHD-2	17856	235	30	24	127	22.5	234.5	28.5	167	678
LHD-3	17856	192	20	18	56	15	56	13.5	49	244
LHD-4	17856	177.5	59	57	137	57	186	70	211.5	844
LHD-5	17856	243	26.5	23	90.5	19.5	64	25.5	54	342

Table 3.10 (b) Idle Hours (IDhr) data of LHDs of study area-2 (in hours)

Machine	Reasons/Causes for Machine being Idle											Total IDhr
	DAC	DSH	DAN	DSC	DBL	DRS	DBR	DDB	DST	DBP	DOT	
LHD-1	60	112	84	106	48	130	50	140	110	535	144	1519
LHD-2	220	50	90	100	210	110	80	240	200	260	244	1804
LHD-3	231	223	160	246	510	120	96	120	164	130	1720	3720
LHD-4	80	96	70	130	140	160	80	49	120	175	388	1488
LHD-5	21	68	90	110	90	129	90	60	100	40	186	1386

Table 3.11 (a) Breakdown hours (BDhr) data of LHDs of study area-3 (in hours)

Machine	SShr	SMhr	Breakdown Hours								Total BDhr
			SSE	SSBr	SSBo	SSTy	SSH	SSEl	SSTr	SSM	
E1-LHD1	14232	542	73	56	127	175	51	302	50	2034	3036
E2-LHD2	11556	354	131	30	38	61	204	114	23	2689	3309
E3-LHD3	13680	570	73	71	56	130	57	243	56	710	1370
E5-LHD5	14328	597	50	48	54	137	37	256	32	515	1139
E6-LHD6	13680	570	84	66	61	129	66	346	29	797	1479

Table 3.11 (b) Idle Hours (IDhr) data of LHDs of study area-3 (in hours)

Machine	Reason/Cause for Machine being Idle											Total IDhr
	DAC	DSH	DAN	DSC	DBL	DRS	DBR	DDB	DST	DBP	DOT	
E1-LHD1	268	332	389	568	380	587	501	367	263	363	2253	6271
E2-LHD2	120	118	280	972	160	355	321	110	264	422	725	3847
E3-LHD3	212	124	306	586	372	500	420	110	340	523	2102	5859
E5-LHD5	284	480	336	679	264	674	332	451	192	638	1837	6201
E6-LHD6	440	160	380	674	184	491	400	410	210	458	1490	5341

In this chapter field investigations for the collection of failure data of LHD machines were discussed. Also the methodology used in this research work has been explained clearly.

CHAPTER-4

RELIABILITY, AVAILABILITY AND MAINTAINABILITY (RAM) STUDY

Reliability prediction is the process of calculating the anticipated system Reliability, Availability, and Maintainability (RAM) with its failure data sets. The current chapter explains the concept of **reliability prediction** of a complex repairable system. In addition to that, an attempt has been made to estimate the reliability-based preventive maintenance time intervals for the enhancement of equipment life.

4.1 CLASSIFICATION OF COLLECTED DATA

Once the data collection is completed, the arrangement/classification procedure needs to be carried out. The collected data from the field investigation has been categorized based on the requirement of the proposed analysis. The categorization of failure and repair data is made by computing the parameters such as Time Between Failure (TBF), Time To Repair (TTR) and Failure Frequency (FF). These computed metrics are helpful to determine the parameters of Cumulative Time Between Failure (CTBF), Cumulative Time To Repair (CTTR) and Cumulative Failure Frequency (CFF). These values are useful to perform the graphical analysis comparing trend and serial correlation tests for validating the Independent and Identical Distribution (IID) nature of the data sets. Further, the prepared data sets of TBF and TTR are useful to perform the Reliability, Availability, and Maintainability (RAM) analysis of the LHD system. The TBF, TTR values were calculated from Equation 4.1 and Equation 4.2 and the computed values along with FF for each sub-system of study area-1 are given in Table 4.1. In respect of study area-2 and study area-3 are given in Table 4.2 and Table 4.3 in Appendix 1. The CTBF, CTTR and CFF are the cumulative values of TBF, TTR and FF and these are computed with the summation of the current value and to its next corresponding value. The CTBF, CTTR and CFF values of study area-1 are given in Table 4.4 and for study area-2 and study, area-3 are given in Table 4.5 and Table 4.6 in Appendix 1.

$$\mathbf{M\quad BF} = \frac{(\quad \mathbf{hr} - \quad \mathbf{Mhr} - \mathbf{BDhr} - \mathbf{IDhr})}{\mathbf{FF}} \qquad (4.\quad)$$

$$\mathbf{M} \qquad = \frac{(\mathbf{BDhr} + \mathbf{IDhr})}{\mathbf{FF}} \qquad (4.\quad)$$

Table 4.1 TBF and TTR data sets of sub-systems of LHDs of study area-1

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LH21	FF (No/.)	8	20	42	24	10	28	35
	TBF (hours)	1804	714	330	595	1436	508	401
	TTR (hours)	388	162	87	135	318	117	100
LH22	FF (No/.)	45	28	16	48	24	34	26
	TBF (hours)	363	590	1036	339	690	483	636
	TTR (hours)	100	127	238	103	152	120	140
LH24	FF (No/.)	38	14	30	28	16	34	45
	TBF (hours)	417	1155	533	575	1012	467	349
	TTR (hours)	166	272	171	180	255	169	110
LH25	FF (No/.)	14	45	27	18	36	10	26
	TBF (hours)	1194	364	615	926	457	1676	640
	TTR (hours)	304	124	210	284	168	356	182
LH26	FF (No/.)	29	28	24	20	24	18	33
	TBF (hours)	563	584	682	882	682	913	492
	TTR (hours)	170	184	210	254	210	310	164
LH27	FF (No/.)	14	18	16	17	32	12	35
	TBF (hours)	1199	929	1047	984	517	1401	470
	TTR (hours)	353	286	323	304	168	389	142
LH28	FF (No/.)	34	16	18	24	32	44	28
	TBF (hours)	489	1047	930	696	516	373	596
	TTR (hours)	158	326	302	174	159	140	164
LH29	FF (No/.)	32	16	18	17	25	20	36
	TBF (hours)	520	1047	922	983	665	836	461
	TTR (hours)	160	326	300	322	175	198	148
LH30	FF (No/.)	16	11	10	12	9	10	16
	TBF (hours)	1009	1477	1625	1352	1805	1622	101
	TTR (hours)	300	389	412	367	446	408	302
LH31	FF (No/.)	28	20	12	20	10	10	24
	TBF (hours)	576	813	1357	813	1628	1630	677
	TTR (hours)	184	298	346	299	402	410	208

Table 4.4 Calculated values of CTBF, CTTR and CFF of study area-1

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LH21	CFF (No/.)	8	28	70	94	104	132	167
	CTBF (hours)	1804	2518	2848	3443	4879	5387	5788
	CTTR (hours)	388	550	637	772	1090	1207	1307
LH22	CFF (No/.)	45	73	89	137	161	195	221
	CTBF (hours)	363	953	1989	2328	3018	3501	4137
	CTTR (hours)	100	227	465	568	720	840	980
LH24	CFF (No/.)	38	52	82	110	126	160	205
	CTBF (hours)	417	1572	2105	2680	3692	4159	4508
	CTTR (hours)	166	438	609	789	1044	1213	1323
LH25	CFF (No/.)	14	59	86	104	140	150	176
	CTBF (hours)	1194	1558	2173	3099	3556	5232	5872
	CTTR (hours)	304	428	638	922	1090	1446	1628
LH26	CFF (No/.)	29	57	81	101	125	143	176
	CTBF (hours)	563	1147	1829	2711	3393	4306	4798
	CTTR (hours)	170	354	564	818	1028	1338	1502
LH27	CFF (No/.)	14	32	48	65	97	109	144
	CTBF (hours)	1199	2128	3175	4159	4676	6077	6547
	CTTR (hours)	353	639	962	1266	1434	1823	1965
LH28	CFF (No/.)	34	50	68	92	124	168	196
	CTBF (hours)	489	1536	2466	3162	3678	4051	4647
	CTTR (hours)	158	484	786	960	1159	1259	1423
LH29	CFF (No/.)	32	48	66	83	108	128	164
	CTBF (hours)	520	1567	2489	3472	4137	4973	5434
	CTTR (hours)	160	486	786	1108	1283	1481	1629
LH30	CFF (No/.)	16	27	37	49	58	68	84
	CTBF (hours)	1009	2486	4111	5463	7268	8890	9902
	CTTR (hours)	300	689	1101	1468	1914	2322	2624
LH31	CFF (No/.)	28	48	60	80	90	100	124
	CTBF (hours)	576	1389	2746	3559	5187	6817	7494
	CTTR (hours)	184	482	828	1127	1529	1939	2147

4.1.1 Failure Frequency (FF)

The LHD system was classified into several sub-systems based on the failure type, and it was observed that from all the study areas each sub-system has **a** different frequency of failures. The frequency of failures of study area-1 with bar-chart is shown in Figure 4.1. Similarly, for study area-2, and 3 these are shown in Figure 4.2 and Figure 4.3 in Appendix 1. From the graphical representation of the bar-charts, it is observed that SSE, SSTr, SSH and SSM are the sub-systems that most frequently failed, and the sub-systems of SSBr, SSEl and SSTy have relatively fewer failures as compared with others.

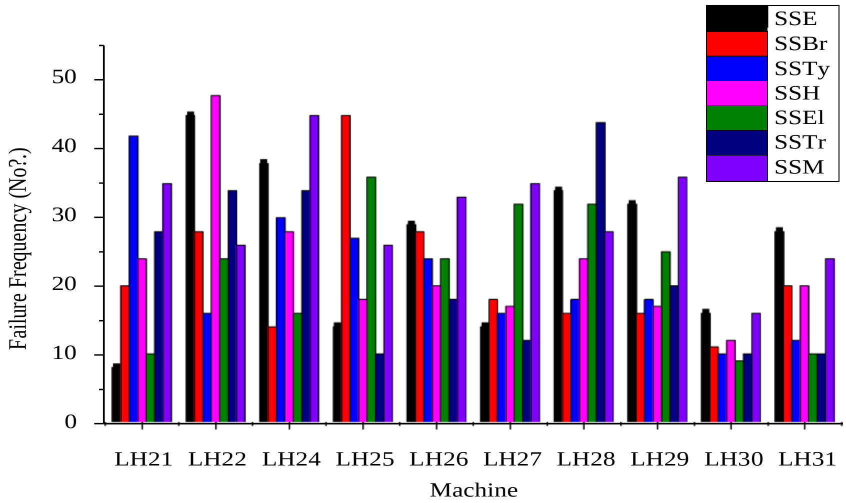


Figure 4.1 FF of sub-systems of LHDs of study area-1

4.2 KEY PERFORMANCE INDICATORS OF LHD

The performance of the equipment can be determined in many ways. The overall equipment performance (OEP) of the machinery mainly depends upon its Key Performance Indicators (KPIs) such as availability and utilization in percentage. Un-availability of the machines at working faces and their in-effective utilization sometimes causes a significant reduction in production, leading to an increase in mine production costs. The projected level of production rate can only be possible by maintaining the equipment efficiently and effectively (Arputharaj, M. E. M. et al., 2015). Percentage availability and capacity utilization of various LHDs were computed by utilizing the collected field failure data. The computed KPIs of study area-1 are given in Table 4.7, and the same is graphically depicted in bar-chart Figure 4.4. Similarly, KPIs for study area-2 and 3 are given in Table 4.8, and Table 4.9, and bar-charts of Figure 4.5 and Figure 4.6 in Appendix 1.

The KPIs (Availability and Utilization in percentage) of LHDs are helpful to measure the performance of equipment. From the computed results of Table 4.7, LH21 (80.67%) system has the highest availability percentage as compared with other systems. Even though the system was having the highest availability percentage, its utilization level was observed as 56.25% only. Similarly, the least availability percentage was identified for the system LH26 (74.75%) and its utilization was about 53.91%. Maximum production and productivity from an LHD are only possible by strict adherence to Preventive Maintenance (PM) schedules, better organization of men and machinery, skilled operating crew. The efficient working of the machine can be obtained by increasing the Machine Available Hours (MAhr) in a planned shift.

Table 4.7 Percentage Availability and Utilization of LHDs of study area-1

Machine	SShr	SMhr	SAhr	BDhr	MAhr	IDhr	MWhr	% Avl.	%Utl.
LH21	17544	167	17377	2180	15197	2873	12324	80.67	56.25
LH22	17544	417	17127	1716	15411	405	15006	78.00	45.55
LH24	17544	273	17271	2308	14963	948	14015	69.99	59.88
LH25	17544	526	17018	1755	15263	151	15112	78.29	56.13
LH26	17544	340	17204	1931	15273	551	14722	74.75	53.91
LH27	17544	391	17153	1582	15571	233	15338	76.92	57.42
LH28	17544	467	17077	1685	15392	190	15202	76.55	56.65
LH29	17544	308	17153	1582	15571	233	15338	77.96	57.42
LH30	17544	219	17325	942	16383	966	15417	79.05	57.87

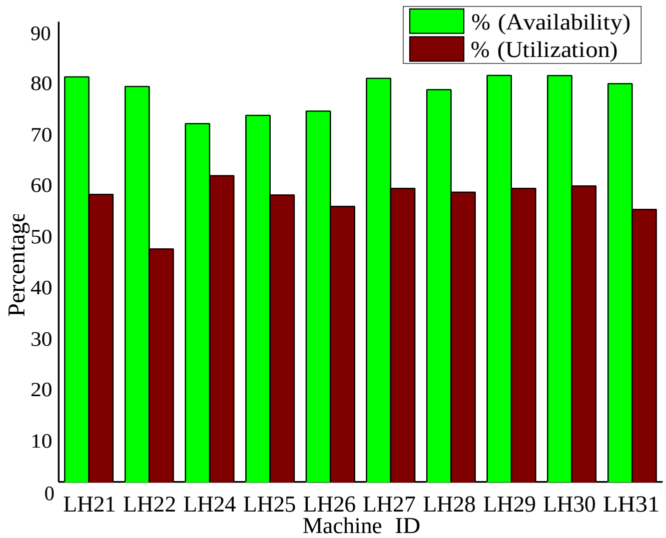


Figure 4.4 Comparison of KPIs of LHDs for study area-1

4.3 VALIDATION OF THE CLASSIFIED DATA

4.3.1 Trend Test and Serial Correlation Test

The trend test for the present study was carried out graphically. In this study, graphical methods such as trend and serial correlation tests were adopted to identify the trend and correlation among the data sets. Before fitting the data, it is necessary to check whether the data has a trend or not, i.e., if the rate of failures for the system is increasing, decreasing or constant. One can observe the trend of the failure data by plotting the CTBF and the number of failures. If the line is concave and downwards it shows that trend exists. If the line is concave and upwards, then it suggests an improving system.

The objective of the serial correlation test is to check the relationship between two variables. The scatter plots between the two variables (i^{th} TBF and $(i-1)^{th}$ TBF) exhibits the correlation between the two variables. Figure 4.7 (a) represents the trend test for CFF and CTBF and correlation i.e., scatter plot test for i^{th} TBF and $(i-1)^{th}$ TBF data of LH21of study area-1, of LHD1 of study area-2, and E1-LHD1 machine of study area-3 respectively. The trend plots of Figure 4.7 (a), 4.17 (a), and 4.22 (a) show that the line is linear, and the maximum points are not passing through the line. This indicates that there is no trend in the data sets. Similarly, the scatter plots of Figure 4.7 (b), 4.17 (b), and 4.22 (b) show that the data are widely scattered, and thus there is no correlation exists between the two consequent failures. This is validating the assumptions of the Independent and Identical Distribution (IID) nature of data sets. In the same way, trend and serial correlation tests were performed for the data sets of remaining machines study area-1 (from Figure 4.8 (a) and (b) to Figure 4.16 (a) and (b)and given in Appendix 1). The results of trend and serial correlation tests for study area-2 (From Figure 4.17 (a) and (b) to Figure 4.21 (a) and (b)), and study area-3 (From Figure 4.22 (a) and (b) to Figure 4.26 (a) and (b)) are given in Appendix 1. From the results of graphical analysis, it was observed that these machineries were not displaying any trend and there is no correlation between the datasets. If the trend and correlation in the system exist, reliability parameters can be calculated through the analytical Homogeneous Poison Process (HPP) approach.

- **Trend and serial correlation test of study area-1:**

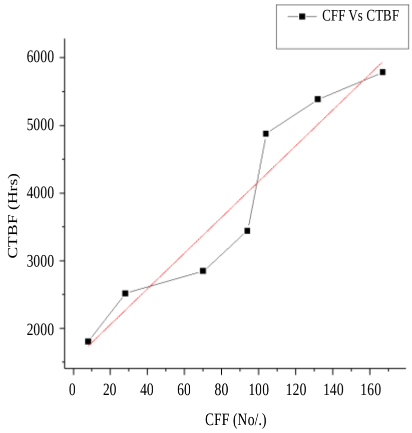


Figure 4.7 (a) Trend test of LH21

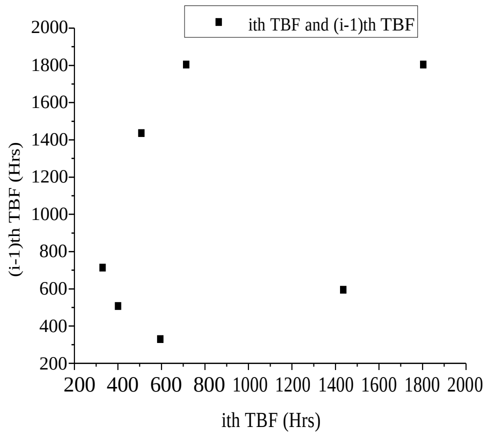


Figure 4.7 (b) Serial correlation test of LH21

- **Trend and serial correlation test of study area-2:**

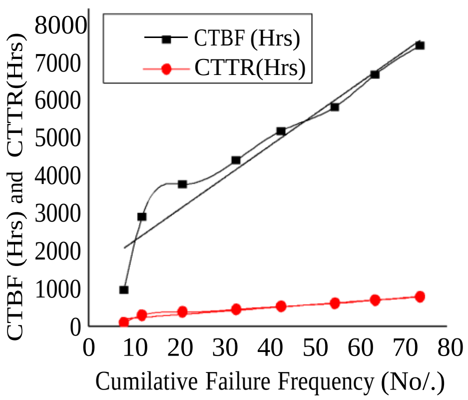


Figure 4.17 (a) Trend test for LHD-1

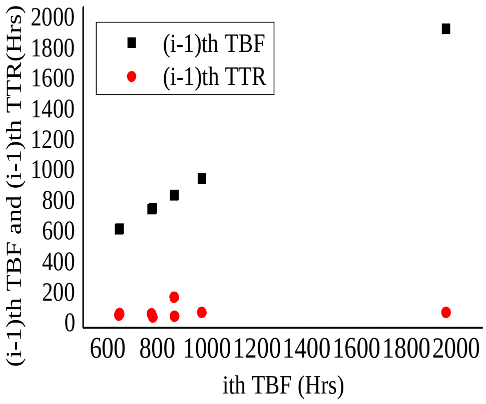


Figure 4.17 (b) Correlation test for LHD-1

- **Trend and serial correlation test of study area-3:**

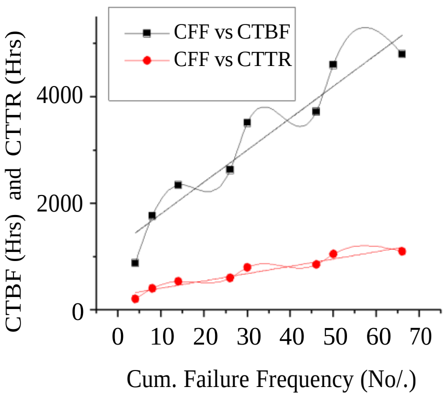


Figure 4.22 (a) Trend test of E1-LHD1

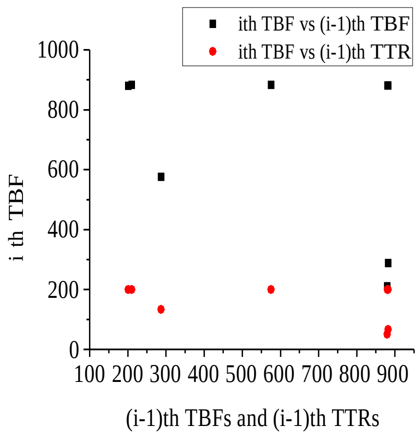


Figure 4.22 (b) Correlation test of E1-LHD1

4.3.2 Statistic U-Test (Chi-Squared Test)

The analytical analysis is another approach for investigating the existence of a trend in the datasets. This approach is used to identify the Independent and Identically Distributed (IID) nature of the data sets. Null-hypothesis of the datasets of LHDs were tested for identification IID nature using the Chi-squared (Statistic U) test. The computed values of the statistic-U test for the various system failures concerning the TBF values of study area-1 are given in Table 4.10. Similarly, the computed results of a statistic-U test of study area-2 are given in Table 4.11 and for study, area-3 are given in Table 4.12 in Appendix 1. It was found that the null hypothesis was not rejected at 5% level of significance in all the systems. The same kinds of results were obtained in the graphical analysis of trend and serial correlation tests. In the trend test, the data set points of all the systems and sub-systems are away from the trend line, whereas, in the case of serial correlation test, the points are randomly scattered, which exhibit no correlation. The results of these graphical tests have shown that the data sets of all the systems are free from the presence of trend and correlation. Hence, the assumption of datasets as independent and identically distributed (IID) in time is valid for these system failures. The reliability modelling method (HPP, NHPP, and RP) has also been used to perform trend free reliability analysis. The statistic-U test values were calculated from Equation 4.3 (Ascher. T. M. 1988 and Kumar U et al., 1992). The calculated values of static-U were tested with a 5% level of significant P-values.

$$U = 2\sum_{i=1}^{n} \ln[\frac{Tn}{Ti}] \qquad (4.3)$$

Where Tn is the nth value of TBF. The data sets are tested for rejection of the null hypothesis at a 5% level of significance with the 2(n-1) degree of freedom (DOF).

From the results, it is noticed that the null hypothesis is not rejected at 5% level of significance. Hence, from the results of graphical and statistical analysis, it is identified that the TBF data sets are trend free with no correlation, and all the machine parameters are independent and identically distributed. As a result of this, the Renewal Process (RP) technique has been suggested to perform the reliability analysis. This analysis has been performed based on the suggested method by utilizing the Isograph reliability Workbench 13.0 software.

Table 4.10 Results of statistic U-test for LHDs of study area-1

Machine	Data set	DOF	Calculated Statistic U	P-value	Rejection of Null Hypothesis at 5% level of significance	Modelling Method
LH21	TBF	332	10.46	1.989	10.46< 35.17 Not rejected	RP
LH22	TBF	440	8.77	0.874	8.77 < 44.99 Not rejected	RP
LH24	TBF	408	9.44	0.912	9.44< 42.56 Not rejected	RP
LH25	TBF	350	11.44	1.782	11.44< 37.65 Not rejected	RP
LH26	TBF	350	4.91	0.466	4.91< 37.65 Not rejected	RP
LH27	TBF	286	6.60	0.617	6.60< 31.41 Not rejected	RP
LH28	TBF	390	4.77	0.423	4.77< 40.11 Not rejected	RP
LH29	TBF	326	4.76	0.426	4.76< 35.17 Not rejected	RP
LH30	TBF	166	3.72	0.378	3.72< 19.68 Not rejected	RP
LH31	TBF	246	6.98	0.698	6.98< 27.59 Not rejected	RP

4.4 KOLMOGOROV-SMIRNOV (K-S) TEST

The goodness-of-fit (best-fit) distribution for TBF datasets has been performed with the Kolmogorov-Smirnov (K-S) approach. The principle behind this is to see, how far the chosen distribution is from the actual dataset, or in other words how well the chosen distribution represents the observed distribution. Four statistical probability distribution functions (Exponential Parameter, 1-Parameter Weibull, 2-Parameter Weibull and 3-Parameter Weibull functions) were examined for modelling the breakdown data of LHDs. These distributions are appropriate for modelling the failures of mechanical systems. The distribution which has the least level of significance (α) among all others is treated as best-fit distribution based on the level of significant value. The parameters of the allocated best-fit distributions were estimated using the Maximum Likelihood Estimate (MLE) method. The K-S test and the parameter estimation of probability distribution functions using MLE were conducted using 'Isograph reliability Workbench 13.0' software. The reliability of each sub-system of LHD has been computed based on the allocated best-fit distributions. The results of the K-S test for the four distributions and the best-fitted distribution for TBF data sets of study area-1 are given in Table 4.13 (a). The estimated parameters of the best-fit distribution function with MLE are presented in Table 4.13 (b). Likewise, the results of K-S test and MLE method of study area-2 are given in Table 4.14 (a) and (b) and for study, area-3 are given in Table 4.15 (a) and (b) in Appendix 1.

Table 4.13 (a) Kolmogorov-Smirnov (K-S) test results of study area-1

Machine	K-S Statistic Dmax				Best Fit Model
	Exponential	Weibull 1P	Weibull 2P	Weibull 3P	
LH21	0.1161	0.1087	0.0915	0.0420	Weibull 3P
LH22	0.1842	0.1638	0.0586	0.0490	Weibull 3P
LH24	0.1691	0.1511	0.1023	0.0533	Weibull 3P
LH25	0.1365	0.1206	0.0585	0.0331	Weibull 3P
LH26	0.2314	0.2075	0.0804	0.0527	Weibull 3P
LH27	0.1857	0.1647	0.0690	0.0000	Weibull 2P
LH28	0.1889	0.1674	0.0635	0.0368	Weibull 3P
LH29	0.2052	0.1834	0.0543	0.0553	Weibull 2P
LH30	0.2331	0.2097	0.0617	0.0577	Weibull 3P
LH31	0.1739	0.1543	0.0899	0.0727	Weibull 3P

Table 4.13 (b) Results of MLE of study area-1

Machine	Best Fit Model	ML Estimates of the Best Fit Parameters (η=Scale/life, β=Shape, γ=Location)		
		η	β	γ
LH21	Weibull 3P	537	0.8054	296.9
LH22	Weibull 3P	365.4	1.218	272.4
LH24	Weibull 3P	348.5	0.9253	319.5
LH25	Weibull 3P	619.4	1.095	283.1
LH26	Weibull 3P	286.4	1.387	438.3
LH27	Weibull 2P	1072	2.492	0
LH28	Weibull 3P	411.2	1.293	307.1
LH29	Weibull 2P	869.6	3.263	0
LH30	Weibull 3P	2326	7.048	-769
LH31	Weibull 3P	672.2	1.105	479.2

4.5 RELIABILITY PREDICTION

4.5.1 Analysis of Data with a Trend

If the TBF datasets of LHDs exhibit the presence of trend in the trend test, then the assumption of IID is not valid for the data sets. These systems should be analyzed by a non-stationary model such as the Non-Homogeneous Poisson process (NHPP). In such a case, the Power Law Process (PLP) based NHPP model is used to compute the reliability parameters of the LHD system. The PLP is a certain form of NHPP model that has been proved as a useful tool for analyzing the systems which are failing or improving with time. Intensity, U(t), of the power-law process (PLP) model is calculated with Equation (4.4) as given below (Kumar. U. et al. 1989):

$$(\ ) = \frac{\beta}{\eta} \times \left\{ \frac{\ }{\eta} \right\}^{\beta-1} \qquad (4.4)$$

Where, η, β are the scale, shape parameters respectively and ‘t’ is the running time.

4.5.2 Analysis of Trend-free Data

The trend-free data sets are further analyzed to determine the accurate characteristics of the LHDs failure time distributions. The idealized probability distributions are commonly used to describe the TBF datasets. A wide variety of statistical distributions were examined to estimate the goodness of fit of data sets, and their parameters were also estimated using ‘Isograph Reliability Workbench 13.0’ software. The software fits an adequate distribution model for the data sets based on the value of the level of significance. The user can then choose a preferred model, or accept the model recommended by the software based on the performed analysis. The software recommended results of best-fitted distributions such as failure rate (FR) and probability density function (PDF) of study area-1 are given in Table 4.16. Similarly, the computed values of FR and PDF for study area-2 (Table 4.17) and study area-3 (Table 4.18) are given in Appendix 1. The respective plots of the FR and PDF of LHDs as per the best fit distribution of study area-1 are illustrated in Figure 4.27 (a) and (b). Similarly, the remaining plots for study area-1 from Figure 4.28 (a) and (b) to Figure 4.36 (a) and (b) are given in Appendix 1. These plots (FR & PDF) for study area-2 (from Figure 4.37 (a) and (b) to Figure 4.42 (a) and (b)) and study area-3 (from Figure 4.43 (a), and (b) to Figure 4.47 (a), and (b)) are also given in Appendix 1.

Table 4.16 Results of FR and PDF of LHDs of study area-1

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LH21	TBF	1804	714	330	595	1436	508	401
	FR	0.00055	0.00139	0.00303	0.00168	0.00069	0.00196	0.00249
	PDF	0.0001	0.0006	0.0024	0.0009	0.0002	0.0011	0.0014
LH22	TBF	363	590	1036	339	690	483	636
	FR	0.00275	0.00169	0.00096	0.00294	0.00144	0.00206	0.00157
	PDF	0.0020	0.0013	0.0003	0.0020	0.0010	0.0017	0.0012
LH24	TBF	417	1155	533	575	1012	467	349
	FR	0.00239	0.00086	0.00187	0.00173	0.00098	0.00213	0.00286
	PDF	0.0021	0.0002	0.0014	0.0012	0.0003	0.0018	0.0029
LH25	TBF	1194	364	615	926	457	1676	640
	FR	0.00083	0.00274	0.00162	0.00107	0.00218	0.00059	0.00156
	PDF	0.0003	0.0013	0.0009	0.0006	0.0012	0.0001	0.0009
LH26	TBF	563	584	682	882	682	913	492
	FR	0.00177	0.00171	0.00146	0.00113	0.00146	0.00109	0.00203
	PDF	0.0025	0.0025	0.0020	0.0008	0.0020	0.0007	0.0023
LH27	TBF	1199	929	1047	984	517	1401	470
	FR	0.00083	0.00107	0.00095	0.00101	0.00193	0.00071	0.00212
	PDF	0.0007	0.0009	0.0008	0.0009	0.0006	0.0004	0.0006
LH28	TBF	489	1047	930	696	516	373	596
	FR	0.00020	0.00095	0.00107	0.00143	0.00193	0.00267	0.00167
	PDF	0.0017	0.0004	0.0006	0.0012	0.0017	0.0016	0.0015
LH29	TBF	520	1047	922	983	665	836	461
	FR	0.00192	0.00095	0.00108	0.00101	0.00150	0.00119	0.00216
	PDF	0.0009	0.0009	0.0012	0.0011	0.0013	0.0014	0.0007
LH30	TBF	1009	1477	1625	1352	1805	1622	1012
	FR	0.00099	0.00067	0.00061	0.00073	0.00055	0.00061	0.00098
	PDF	0.0005	0.0011	0.0010	0.0010	0.0007	0.0010	0.0005
LH31	TBF	576	813	1357	813	1628	1630	677
	FR	0.00017	0.00122	0.00073	0.00122	0.00061	0.00061	0.00147
	PDF	0.0011	0.0009	0.0004	0.0009	0.0002	0.0002	0.0011

Plots of FR, and PDF of study area-1:

LH21 Failure Rate

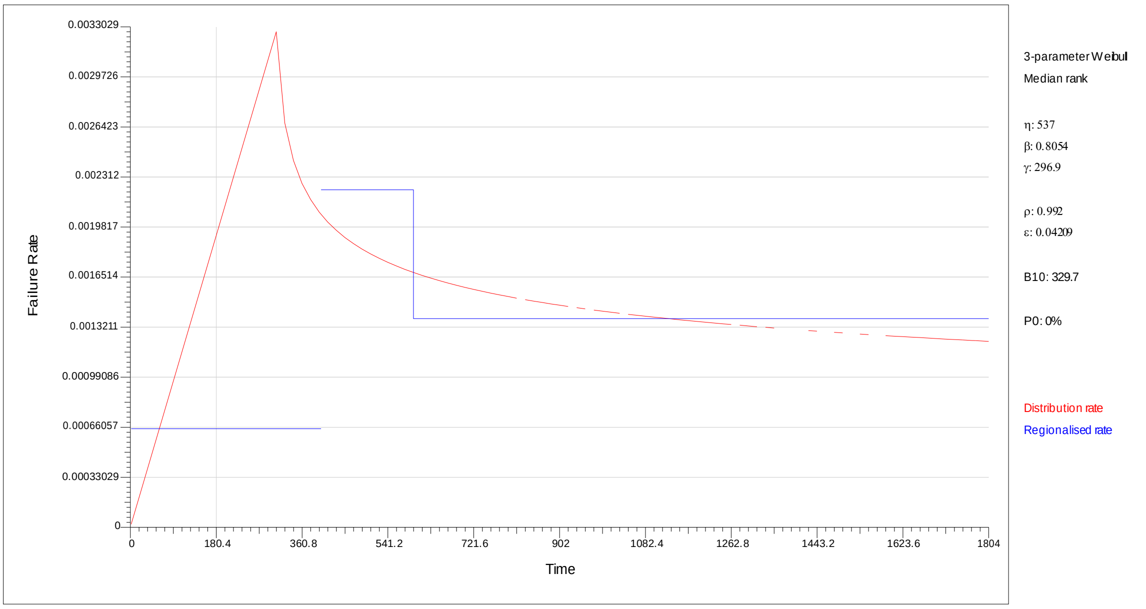


Figure 4.27 (a) FR of LH21

LH21 Probability Density Function

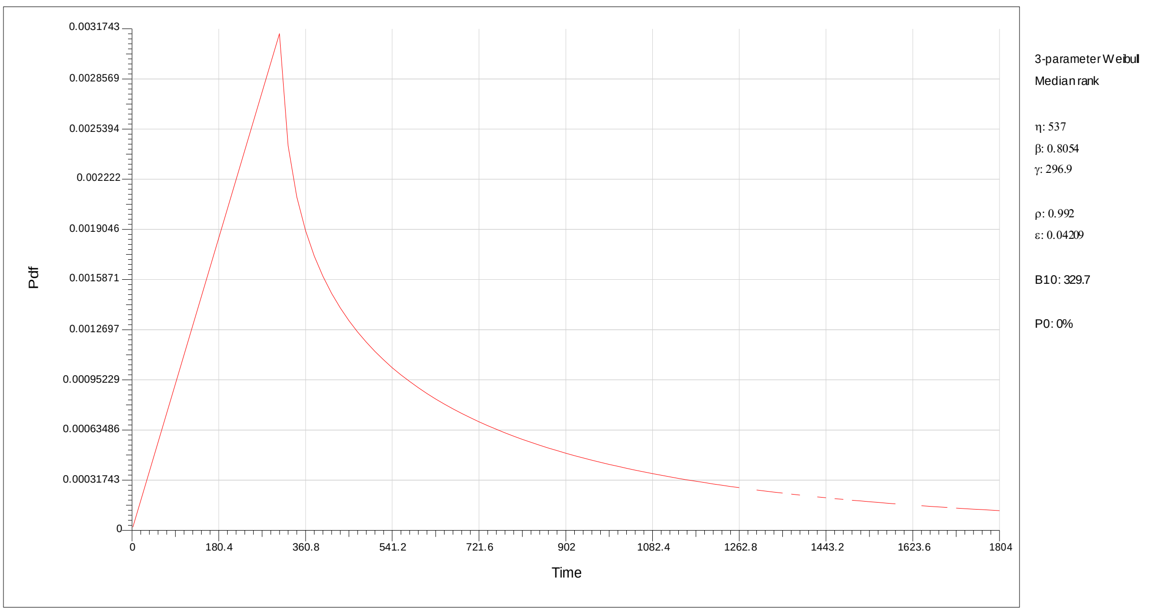


Figure 4.27 (b) PDF of LH21

4.5.3 Estimation of Reliability and Unreliability

Reliability is defined as the probability of a machine or its components to perform its designated job under the given circumstances (Bala. J. et al. 2018). The reliability of each subsystem of the LHD system was determined based on the allocated best-fit distribution using 'Isograph Reliability Workbench 13.0'. The following empirical relations (Equation 4.5 and 4.6) are used to estimate the reliability of each sub-system. In the present study, these values were estimated according to the best fit distribution. The equation of cumulative density function (*cdf)* for the 3-parameter Weibull distribution is (Ahmad, M. et al., 2009, and Dolas, D. et al., 2014):

$$F(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{4.5}$$

It can also be stated as unreliability and nominated as Q(t). The reliability function of a distribution can be taken as one minus the cdf. The reliability function for the 3-parameter Weibull distribution is:

$$R(t) = e^{-\left[\frac{t-\gamma}{\eta}\right]^{\beta}} \times 100 \tag{4.6}$$

Where R(t) denotes reliability of the system for a specified time t, η indicates scale parameter, β indicates shape parameter and γ indicates the location parameter of the best-fit distribution of a system. If the best fit distribution is a 2-parameter Weibull, then the location parameter (γ) is considered as zero. The percentage of un-reliability and reliability of each subsystem of LHDs for TBF data sets of study area-1 are given in Table 4.19. Similarly, the reliability and unreliability values for study area-2 (Table 4.20) and study area-3 (Table 4.21) respectively are given in Appendix 1.

From the sub-system wise reliability analysis (Table 4.19), least percentage of reliability for the sub-system SSE was observed for LH25 (21.73%) and similarly LH24 (20.56%) for SSBr, LH28 (28.06%) for SSTy, LH26 (20.95%) for SSH, LH21 (16.00%) for SSEl, LH26 (20.26%) for SSTr and LH22 (36.94%) for SSM. It was observed that the least value of reliability was observed for sub-system SSEl, SSTy, SSH and SSTr ranging 16.00% to 20.96 %. It seems that SSEl, SSTy, SSH and SSTr are the more critical as compared with other subsystems. The unexpected occurrence of frequent failures and the gap between each successive failure leads to a reduction in the level of reliability. The reliability of a repairable system mainly depends on its design, operation and maintenance credentials. Therefore, it is recommended that more attention needs to be paid to the sub-systems of SSEl, SSTy, SSH and SSTr.

Table 4.19 Percentage of reliability and unreliability of LHDs of study area-1

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LH21	TBF	1804	714	330	595	1436	508	401
	Q%	66.27	55.78	10.06	46.34	84.00	37.67	23.42
	R%	33.73	44.22	89.94	53.66	16.00	62.33	76.58
LH22	TBF	363	590	1036	339	690	483	636
	Q%	16.71	56.97	71.44	11.91	69.25	40.17	63.05
	R%	83.28	43.02	28.56	88.08	30.74	59.82	36.94
LH24	TBF	417	1155	533	575	1012	467	349
	Q%	26.65	79.43	47.07	52.77	64.86	36.39	9.67
	R%	73.34	20.56	52.92	47.22	35.14	63.60	90.32
LH25	TBF	1194	364	615	926	457	1676	640
	Q%	78.26	10.21	39.68	64.74	22.13	71.19	42.19
	R%	21.73	89.78	60.31	35.25	77.86	28.81	57.80
LH26	TBF	563	584	682	882	682	913	492
	Q%	27.24	32.50	55.20	79.05	55.18	79.74	9.38
	R%	72.75	67.49	44.79	20.95	44.81	20.26	90.61
LH27	TBF	1199	929	1047	984	517	1401	470
	Q%	73.33	50.38	61.07	55.47	15.00	75.77	12.06
	R%	26.66	49.61	38.92	44.52	84.99	24.23	87.93
LH28	TBF	489	1047	930	696	516	373	596
	Q%	29.48	78.21	71.93	60.64	34.15	9.03	46.97
	R%	70.51	21.78	28.06	39.35	65.84	90.96	53.02
LH29	TBF	520	1047	922	983	665	836	461
	Q%	17.11	74.00	60.29	67.55	34.09	58.57	11.88
	R%	82.88	25.99	39.70	32.44	65.90	41.42	88.11
LH30	TBF	1009	1477	1625	1352	1805	1622	1012
	Q%	14.00	54.24	60.70	40.72	77.06	60.36	14.13
	R%	85.99	45.75	39.29	59.28	22.93	39.63	85.86
LH31	TBF	576	813	1357	813	1628	1630	677
	Q%	11.14	37.01	63.90	37.04	73.61	73.66	22.87
	R%	88.85	62.98	36.09	62.95	26.38	26.33	77.12

4.6 DETERMINATION OF AVAILABILITY AND MAINTAINABILITY

Elevli. S and Elevli. B (2010) and Sivaselvam. E, and Gajendran. S (2014), have defined 'Availability' as the percentage of time during which equipment is capable of performing its specified functions compared to the total number of available hours in a given period. In other words, availability is simply defined as the proportion of time the equipment is ready to be used for its intended purpose (Paterson, W., and Knights. P. 2012 and Ram Prasad Chaudhary. 2015). 'Maintainability' is the probability that a unit or system will be restored to specified conditions within a given period when appropriate maintenance action is taken by prescribed procedures and resources (Dhillon. B. S. 2008). The availability and maintainability percentages are calculated from Equations 4.7 and 4.8:

$$Availability(A) = \frac{MTBF}{[MTBF + MTTR]} \times 100 \tag{4.7}$$

$$Maintainability\ (M) = 1 - e^{-\left\{\frac{1}{MTTR}\right\}} \times 100 \tag{4.8}$$

Where MTBF and MTTR are the mean time between failure and mean time to repair. The value of MTBF is calculated as the ratio of CTBF and CFF. Similarly, MTTR is estimated as the ratio of CTTR and CFF. The calculated values of the percentage of availability and maintainability for MTBF and MTTR for study area-1 are given in Table 4.22. The computed results of availability and maintainability for study area-2 and study area-3 are given in Appendix 1 (from Figure 4.23 to Figure 4.24).

Table 4.22 Results of percentage availability and maintainability of study area-1

Machine	Total number of failures	MTBF (hours)	MTTR (hours)	Availability (%)	Maintainability (%)
LH21	167	32.65	7.82	80.67	96.73
LH22	221	15.71	4.43	78.00	99.53
LH24	205	21.99	9.45	69.99	97.53
LH25	176	33.36	9.25	78.29	96.57
LH26	176	25.26	8.53	74.75	99.23
LH27	144	45.46	13.64	76.92	99.99
LH28	196	23.70	7.26	76.55	99.46
LH29	164	35.13	9.93	77.96	99.99
LH30	84	117.88	31.23	79.05	98.18
LH31	124	60.43	17.31	77.73	98.26

4.7 ESTIMATION OF PREVENTIVE MAINTENANCE (PM) TIME INTERVALS

PM is defined as the set of maintenance activities performed in an attempt to keep or retain the machine/equipment in a satisfactory operating condition and to avoid the occurrence of early failure through periodic inspections, lubrication, calibration, repair and replacement actions (Mohammad, J. et al. 2013). Forecasting of preventive maintenance (PM) time intervals is very essential to improve the reliability as well as reduce the failure rate of any kind of system or sub-system. In this study, these intervals were computed for the expected percentage of reliability as shown in Table 4.25. From the computed results of study area-1, it is understood that for having the reliability of 90% for LH21, the PM should be performed after every 538 hours. Similarly, for LH22 to LH31 these are 367, 349, 620, 288, 1072, 412, 870, 1257 and 673 hours respectively. The PM time intervals were also computed for study area-2, and study area-3, and are given in Table 4.26, and Table 4.27 in Appendix 1.

Table 4.25 Preventive Maintenance time intervals for various LHDs of study area-1

Reliability Level	**Maintenance Interval, hours**									
	LH21	**LH22**	**LH24**	**LH25**	**LH26**	**LH27**	**LH28**	**LH29**	**LH30**	**LH31**
Distribution	3P W	3P W	3P W	3P W	3P W	2P W	3P W	2P W	3P W	3P W
Parameters	η= 537 β= 0.8054 γ= 296.9	η= 365.4 β= 1.218 γ= 272.4	η= 348.5 β= 0.9253 γ= 319.5	η= 619.4 β= 1.095 γ= 283.1	η= 286.4 β= 1.387 γ= 438.3	η= 1072 β= 2.492 γ= 0	η= 411.2 β= 1.293 γ= 307.1	η= 869.6 β= 3.263 γ= 0	η= 2326 β= 7.048 γ= -769	η= 672.2 β= 1.105 γ= 479.2
0.90	538	367	349	620	288	1072	412	870	1257	673
0.80	1007	640	628	1287	495	2009	846	1560	2468	1299
0.70	1237	809	789	1455	668	2489	1160	1890	2860	1501

Reliability modelling is the process of predicting or understanding the reliability of a component or system before its actual/field implementation. The subsequent chapter discusses the concept of operational reliability. This helps to identify the overall system reliability, remaining useful life of the equipment. Also identify the influencing factors for performance drop of LHDs using reliability modelling techniques such as reliability Block Diagram (RBD), Fault Tree Analysis (FTA) and Failure Mode and Effect Analysis (FMEA).

CHAPTER-5

RELIABILITY MODELLING TECHNIQUES

5.1 RELIABILITY BLOCK DIAGRAM (RBD) TECHNIQUE FOR ESTIMATION OF OVERALL SYSTEM RELIABILITY

Reliability Block Diagram (RBD) is a systematic deductive method to evaluate the overall system reliability. RBD is a graphical analysis of the logical structure of the system, in which connections of individual sub-systems or parts exist. This method allows the representation of all possible ways for the successful operation of the system. The integrated operation of all the components is necessary for the successful performance of the system (Ahlawat, N. et. al. 2019). There are several methods available in the RBD for evaluation of the process. Depending upon the system configuration, a wide variety of simple Boolean-methods such as parallel, series, the combination of parallel and series and K-out-of-N systems, etc. are used to determine the overall system reliability (ORs) (Kostina, M.et al. 2012).

The concepts of arithmetic and logical statements have been utilized for the estimation of the overall system reliability of a complex system. The reliability-wise relationship of the components in a system can be represented graphically with RBD. The configuration of RBD must be the same as that of the physical connectivity of the components/parts. It's also important to note that reliability depends on the time, that is, reliability of 0.1 means that a component has a 90% probability of failure during a specified operational period. The estimation of overall system reliability for any kind of item/part is only possible by performing the analysis either in a series configuration system or parallel configuration system. For example, a truck is having 4 tires. If one of the tyres undergoes failure, it creates/ increases the extra load on the other tires. If the entire system fails due to the system does not have any redundancy or ability to operate (Example: Aircraft engines). This is represented by the components that are connected in a series configuration. If the system includes redundancy or the ability to operate in a degraded mode, then the model is a bit more complex and the components are connected in a parallel configuration.

In RBD analysis, the utilization of series and parallel arrangement of structures can be made advantageous to the individual elements or groups of elements for estimation of overall system reliability. Each element is characterized by a failure rate. A series arrangement fails if any one of its elements fails. Parallel paths are redundant, that is, all elements must fail for the parallel network to fail. If the probabilities of individual events are known, one can calculate the failure probability of the system (Mencik, J. 2016). In this analysis, the reliability-wise relationship of the connections was identified as all the sub-systems/components are connected in a series configuration. Therefore, the reliability of the systems was estimated with series configuration calculations. Following empirical relations from Equation 5.1 to Equation 5.3 are the developed mathematical models for the estimation of overall system reliability (R_S).

$$(\ ) = {}^{-(\frac{t \quad E = \quad E}{\eta \quad E})^{E}} \times {}^{-(\frac{t \quad r = \quad r}{\eta \quad r})^{r}} \times {}^{-(\frac{t \quad = \quad}{\eta})} \times {}^{-(\frac{t \quad H = \quad H}{\eta \quad H})^{H}} \times {}^{-(\frac{t \quad El = \quad El}{\eta \quad El})^{El}} \times {}^{-(\frac{t \quad r = \quad r}{\eta \quad r})^{r}} \times {}^{-(\frac{t \quad M = \quad M}{\eta \quad M})^{M}} \tag{5.1}$$

$$(\ ) = \quad \times \quad \times \quad \times \quad {}_H \times \quad {}_l \times \quad \times \tag{5.2}$$

$$(\quad) = \prod^{n} y \quad y_{i=1} \quad \times 100 \tag{5.3}$$

Where Rs denotes overall system reliability, i indicates the number of sub-systems i.e., 1, 2, 3….n and Ri indicates the reliability of each sub-system.

The developed mathematical models for LH21 of study area-1 are given in Equation 5.4 to Equation 5.6 and the remaining LH22 to LH31 equipments are given in Equation 5.7 to Equation 5.33 (in Appendix-2). Similarly, the developed models for LHD1 of study area-2 are given in Equation 5.34 to Equation 5.36 and the remaining LHD2 to LHD5 machines are given in Equation 5.37 to Equation 5.48 (in Appendix-2) and Likewise, the developed models for E1-LHD1 of study area-3 are given in Equation 5.49 to Equation 5.51 and the remaining E2-LHD2 to E6-LHD6 equipments are given in Equation 5.52 to Equation 5.63 (in Appendix-2)

$$
{}_{21}(\ ) = -(\frac{1804-296.9}{537})^{0.8054} \times -(\frac{714-296.9}{537})^{0.8054} \times -(\frac{330-296.9}{537})^{0.8054} \times -(\frac{595-296.9}{537})^{0.8054}
$$

$$
\times -(\frac{1436-296.9}{537})^{0.8054} \times -(\frac{508-296.9}{537})^{0.8054}
$$

$$
\times -(\frac{401-296.9}{537})^{0.8054} \quad (5.4)
$$

$$
{}_{21}(\ ) = 0.3373 \times 0.4422 \times 0.8994 \times 0.5366 \times 0.1600 \times 0.6233 \times 0.7658 \quad (5.5)
$$

$$
(\ {}_{21}) = \prod^{n}_{i=1} \frac{y}{y} \times 100
$$

$$
= 69.11\% \quad (5.6)
$$

$$
{}_{H\ 1}(\ ) = -(\frac{1615-68.3}{29.88})^{0.8365} \times -(\frac{2021-68.3}{29.88})^{0.8365} \times -(\frac{897-68.3}{29.88})^{0.8365}
$$

$$
\times -(\frac{1614-68.3}{29.88})^{0.8365} \times -(\frac{1153-68.3}{29.88})^{0.8365} \times -(\frac{4046-68.3}{29.88})^{0.8365}
$$

$$
\times -(\frac{1008-68.3}{29.88})^{0.8365} \quad (5.34)
$$

$$
{}_{H\ 1}(\ ) = 0.5373 \times 0.3492 \times 0.7944 \times 0.4942 \times 0.3268 \times 0.6376 \times 0.5377 \quad (5.35)
$$

$$
(\ {}_{H\ 1}) = \prod^{n}_{i=1} \frac{y}{y} \times 100
$$

$$
= 64.77\% \quad (5.36)
$$

$$
{}_{1-\ H\ 1}(\ ) = -(\frac{881-0}{162.9})^{1.541} \times -(\frac{883-0}{162.9})^{1.541} \times -(\frac{288-0}{162.9})^{1.541} \times -(\frac{883-0}{162.9})^{1.541}
$$

$$
\times -(\frac{211-0}{162.9})^{1.541} \times -(\frac{880-0}{162.9})^{1.541}
$$

$$
\times -(\frac{2012-0}{162.9})^{1.541} \quad (5.49)
$$

$$
{}_{1-\ H\ 1}(\ ) = 0.6922 \times 0.3834 \times 0.4099 \times 0.7222 \times 0.8167 \times 0.5112 \times 0.5564 \quad (5.50)
$$

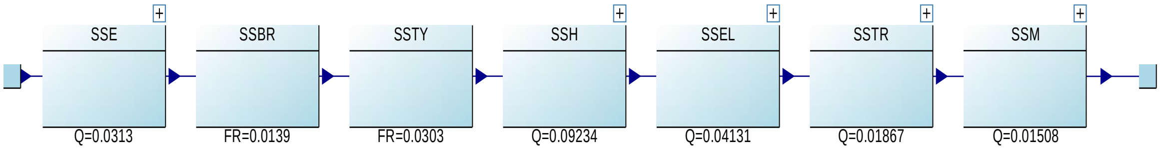
$$
(\ {}_{1-\ H\ 1}) = \prod^{n}_{i=1} \frac{y}{y} \times 100
$$

$$
= 84.77\% \quad (5.51)
$$

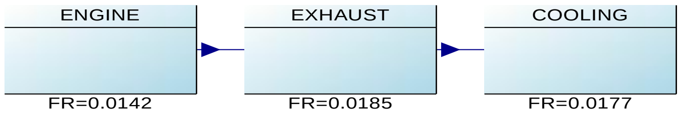
The series-configuration of RBD for the LH21 system of study area-1 is shown in Figure 5.1. The example of series configured RBDs for LH22 is shown in Appendix I (Figure 5.2). Similarly, the examples of series configured RBDs for study area-2 and study area-3 are illustrated in Appendix-2 (Figure 5.3 and Figure 5.4) and (Figure 5.5 and Figure 5.6 respectively). The computed results of overall system reliability percentages of LHDs of study area-1 are given in Table 5.1. Similarly, the computed results of the percentage of overall system reliability of LHDs for study area-2 and study area-3 are given in Table 5.2, and Table 5.3 in Appendix-2. The percentage variation of computed results of LHDs for study area-1 are shown in comparative studies of Figure 5.7 (sub-system) and Figure 5.8 (system). Similarly, for study area-2 (Figure 5.9 and Figure 5.10) and study area-3 (Figure 5.11 and Figure 5.12) are shown in Appendix-2. The examples of percentage variation in predicted values of un-reliability for TBFs from 'Isograph Reliability Workbench 13.0'of study area-1 are shown in time block profile figures from Figure 5.13 and Figure 5.14. Similarly, for study area-2 (Figure 5.15 and Figure 5.16) and study area-3 (Figure 5.17 and Figure 5.18) are also shown in Appendix-2. Fussell-Vesely Importance graphs were also provided for study area-1 to estimate the influencing part of the system towards performance drop (Figure 5.19 and Figure 5.20). Similarly, Fussell-Vesely Importance graphs for study area-2 (Figure 5.21 and Figure 5.22) and 3 (Figure 5.23 and Figure 5.24) are shown in Appendix-2. An example of a results summary screenshot for LH21 (study area-1) is given in Figure 5.25. Similarly, the screenshot results for study area-2 and 3 are shown in Figure 5.26 and Figure 5.27.

From the computed results of overall system reliability (ORs) (Table 5.1) of study area-1, the overall system reliability was maximum for LH29 (69.44%) and minimum for LH24 (56.77%). Similarly, for study area-2 the overall system reliability was maximum for LHD3 (87.49%), and the minimum for LHD1 (64.77%) (Table 5.2). For study area-3 the overall system reliability was maximum for E3-LHD3 (88.09%) and minimum for E4-LHD4 (68.87%) (Table 5.3). From the graphical analysis, it was observed that the sub-systems of SSTr, SSEl, SSH, and SSM were identified as critical components leading to frequent potential LHD machine failure. It is recommended that more concentration/ focus is necessary on these critical parts to minimize system failure. The computed results showed that the machines were not maintained appropriately. Unavailability of the machine in its working state and its in-effective utilization causes a harsh reduction in production levels. This can be improved by strict adherence to PM schedules, better organization of men and machinery, skilled operating crew and well-maintained equipment (Chauhan, S. K and Malik, S. C. 2016). The efficient working of the machine can be obtained by increasing the Available Machine Hours (AMHs) in a planned shift.

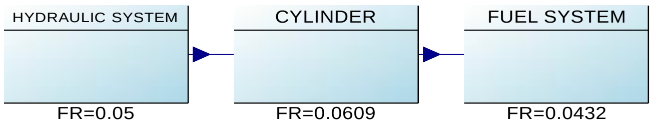
The reliability block diagram (RBD) can be converted into a fault tree. Fault tree analysis (FTA) strives to reveal all the possible sources of critical failures. It starts from the most critical event (“top event”) and looks at its reasons, and continues in this way back to the initial events leading finally to the failure. FTA is useful not only in giving a visual representation of the system but also provides a foundation for identifying and combining probabilities of different events impacting system failure through Boolean logic statements (Bedford. Tim and Roger. Cooke 2001).



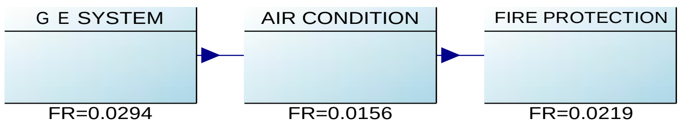
Engine Subsystem:



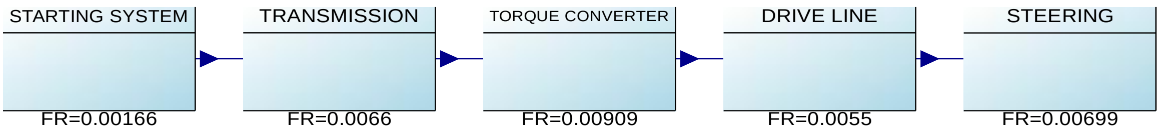
Hydraulic Subsystem:



Electrical Subsystem:



Transmission Subsystem:



Mechanical Subsystem:

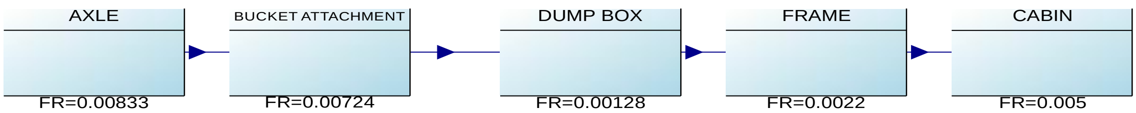


Figure 5.1 Reliability Block Diagram (RBD) of LH21

Table 5.1 Reliability results of each sub-system of LHDs of study area-1

Machine	Sub-system Reliability							System Reliability (%)
	SS E	SS Br	SS Ty	SS H	SS El	SS Tr	SS M	
LH 21	33.73	44.22	89.94	53.66	16.00	62.33	76.58	69.11
LH 22	83.28	43.02	28.56	88.08	30.74	59.82	36.94	66.48
LH 24	73.34	20.56	52.92	47.22	35.14	63.60	90.32	56.77
LH25	21.73	89.78	60.31	35.25	77.86	28.81	57.80	60.03
LH26	72.75	67.49	44.79	20.95	44.81	20.26	90.61	59.98
LH27	26.66	49.61	38.92	44.52	84.99	24.23	87.93	68.65
LH28	70.51	21.78	28.06	39.35	65.84	90.96	53.02	65.63
LH29	82.88	25.99	39.70	32.44	65.90	41.42	88.11	69.44
LH30	85.99	45.75	39.29	59.28	22.93	39.63	85.86	69.41
LH31	88.85	62.98	36.09	62.95	26.38	26.33	77.12	67.24

`

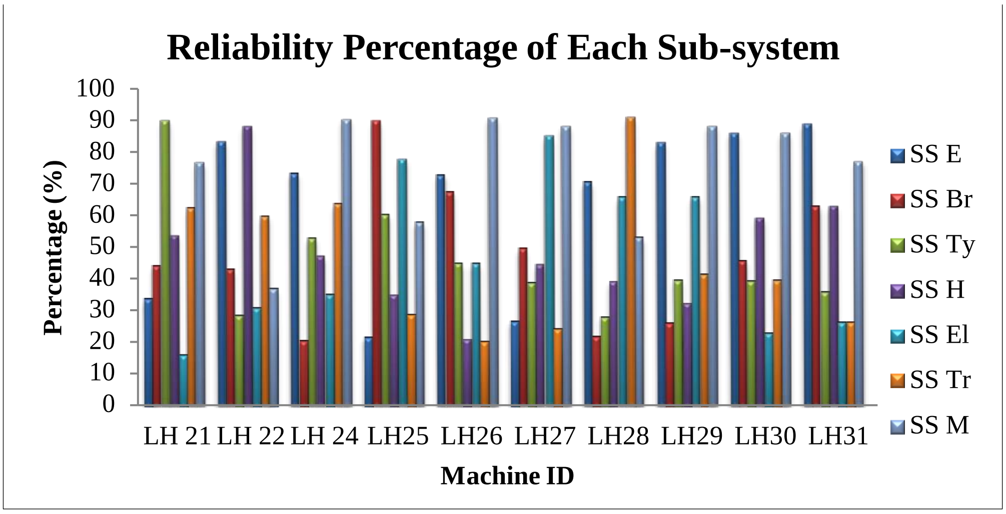


Figure 5.7 Reliability percentage of each sub-system of LHDs of study area-1

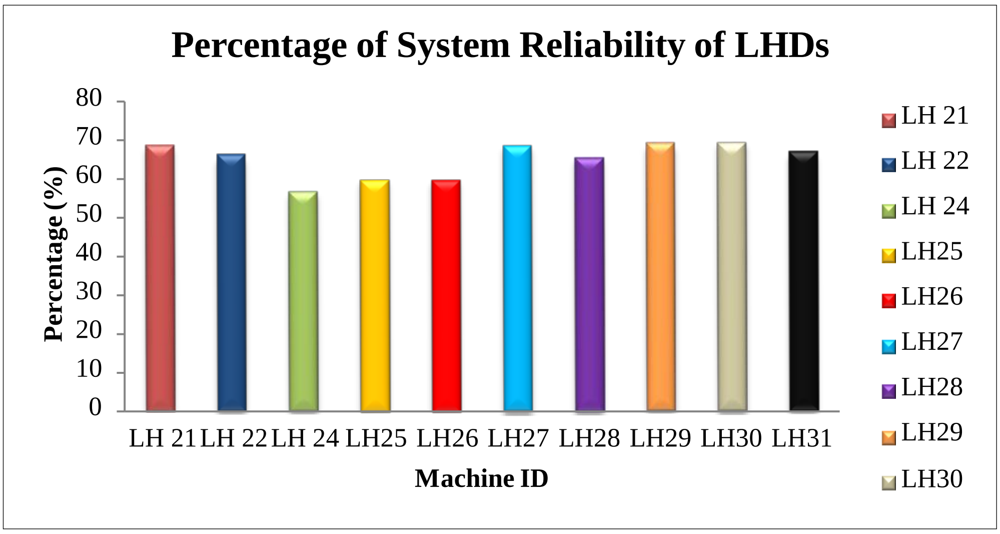


Figure 5.8 Percentage of system reliabilities of LHDs of study area-1

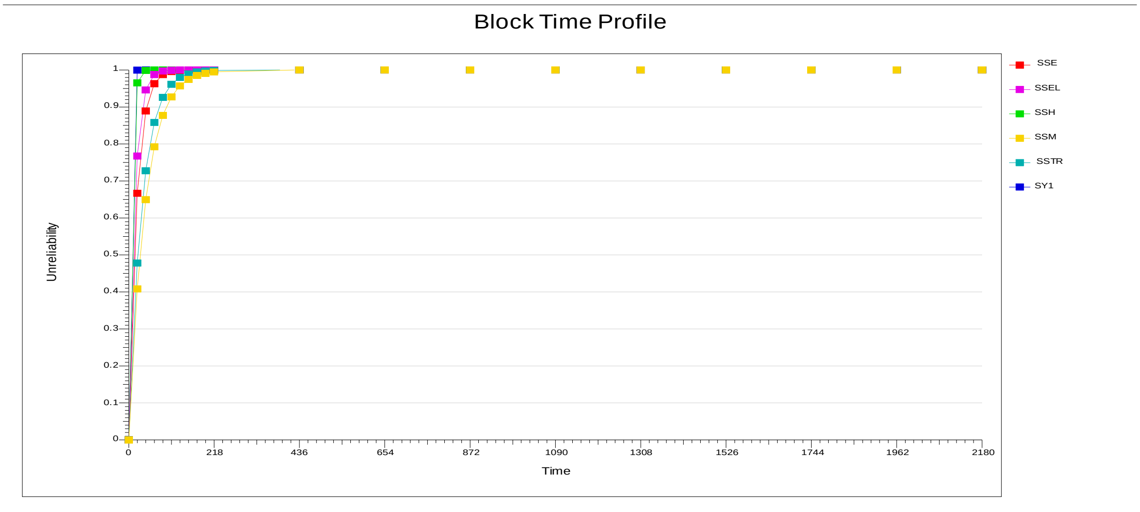


Figure 5.13 System unreliability of LH21 data sets of study area-1

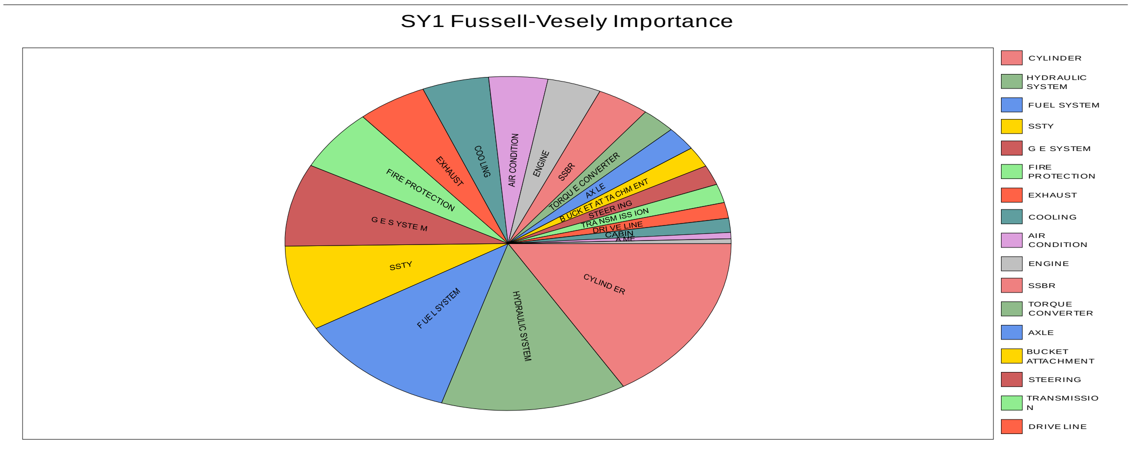


Figure 5.19 Fussell-Vesely Importance of LH21 in pie-chart of study area-1

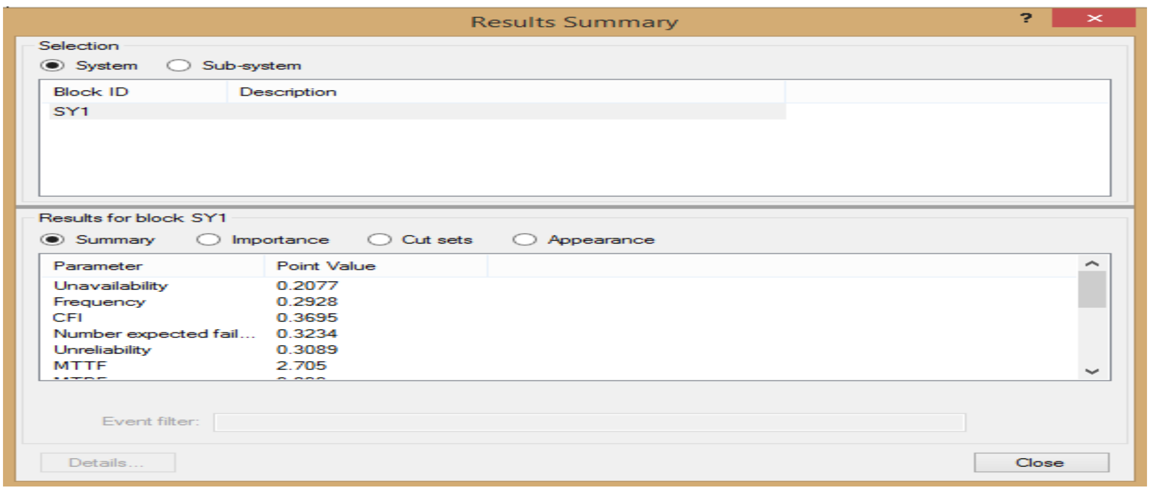


Figure 5.25 An example of results summary screenshot for LH21 of study area-1

5.1.1 Reliable Life Estimation of LHDs

Reliable life is the remaining useful life of the equipment during which it performs its intended function prior (threshold) to the occurrence of failure. The reliable life T_R (Equation 5.64), of a machine for a particular reliability ORs, beginning the work at age zero, is:

$$= \quad + \eta \{-\ln(\qquad)\}^{\frac{1}{}} \qquad (5.64)$$

The productive life of the equipment can be achieved in this reliable lifetime period. If the overall system reliability (ORs) of the equipment is 0.50, then the reliable life (T_R) is treated as the median life (T). The system will survive within this period without the occurrence of a single failure (Kumar. U. 1989). Reliable life T_R of each LHD system has been computed by the overall system reliability (ORs).

Table 5.4 Results of reliable life for each LHD of study area-1

Machine	**System Reliability, ORs**	**Best Fit Distribution**	**Scale Parameter, η**	**Shape Parameter, β**	**Location Parameter, γ**	**Reliable Life, T_R(hours)**
LH 21	69.11	Weibull 3P	537	0.8054	296.9	834.23
LH 22	66.48	Weibull 3P	365.4	1.218	272.4	668.54
LH 24	56.77	Weibull 3P	348.5	0.9253	319.5	447.52
LH25	60.03	Weibull 3P	619.4	1.095	283.1	618.19
LH26	59.98	Weibull 3P	286.4	1.387	438.3	615.24
LH27	68.65	Weibull 2P	1072	2.492	0	724.09
LH28	65.63	Weibull 3P	411.2	1.293	307.1	518.16
LH29	69.44	Weibull 2P	869.6	3.263	0	638.36
LH30	69.41	Weibull 3P	2326	7.048	-769	1247.18
LH31	67.24	Weibull 3P	672.2	1.105	479.2	770.48

From the estimated results of study area-1, it was understood that the reliable life of LH21 was observed as 834.23 hours and for the other machines are given in Table 5.4. Likewise, the least value of T_R was noticed for LH22 (447.52 hours) and the highest value was noticed for LH30 (1247 hours). The vitiation in ORs percentage is the reason for obtaining the least and highest T_R values for the equipment. This means that within a scheduled time interval the LH21 will work without failure for its intended job up to 834.23 hours. After the completion of this period, the first failure is expected to happen. This duration/period can be improved by minimizing the uneven or unplanned breakdowns through the adoption of optimal preventive maintenance schedules. It is recommended that the reliable life of the equipment should estimate periodically from the deposition time for the identification of remaining useful life. The results of computation for equipment's reliable life for study area-2 (Table 5.5), and study area-3 (Table 5.6) are also given in Appendix-2.

5.2 FAULT TREE ANALYSIS (FTA) TECHNIQUE FOR ESTIMATION OF OVERALL SYSTEM AVAILABILITY

FTA is another well understood, and established technique extensively used to determine the unavailability of the system in reliability modelling (Vesely, W. E. et al. 1981). The FTA tool deals with determination and analysis of conditions and factors that cause an occurrence of a previously defined undesired event, that significantly affects the operation, safety, economy or other prescribed parameter of the system (Karacan, C. O and Goodman, G. V. 2008). In this analysis, the logical relationships between breakdowns and their potential causes are represented graphically in a tree-shaped structure. FTA is a deductive method; in that, the analysis starts with a top event (a system failure) and works backward from the top event towards the end gate event to determine the root causes of the top event failure. The results of the analysis show how different components failures or certain environmental conditions can combine, to cause a system failure. After successful completion of the construction of a fault tree diagram, the investigation is performed in two different stages: a quantitative stage, and a qualitative stage.

In quantitative analysis, the probability of the occurrence of the top event and other quantitative reliability indices such as importance measures are mathematically calculated, given the failure rate or probability of individual system components. The results of the quantitative analysis indicate analysts on the available percentage of the system and also help to determine which components or parts of the system are more critical. According to this, the maintenance crew can place more importance on the critical components by taking suitable repair/replacement decisions on time. As the outcome of quantitative analysis is entirely dependent on the accuracy of the statistical data used in the analysis, if uncertainties are left unresolved then there is a possibility of ambiguous results. On the other hand**,** qualitative analysis is generally carried out through reducing fault trees to minimal cut sets (MCSs), which are a disjoint sum of products consisting of the least arrangements of essential events that are necessary and sufficient to cause the top event.

In this study, FTA was carried out to forecast the unavailability of the LHDs and used to identify the most influencing parts/components on system failure. A sample of a fault tree diagram for study area-1 with the data sets of numerous failures of all the sub-systems of LH21 and LH22 are shown in Figure 5.28 and Figure 5.29 (Appendix-2). Similarly, sample diagrams of fault tree analysis of study area-2 (Figure 5.30 and Figure 5.31) and study area-3 (Figure 5.32 and Figure 5.33) are given in Appendix-2. The overall system availability percentage of various systems was estimated using the 'Isograph Reliability Workbench 13.0' software and the percentage of variation was estimated with analytically computed results (Table 5.7). Similarly, results of study area-2 (Table 5.8), and study area-3 (Table 5.9) are given in Appendix-2. The samples of graphical representation of the percentage of unavailability of LH21 and LH22 with the 'Gate Time Profile' of study area-1 are shown in Figure 5.34 and Figure 5.35 (Appendix-2). Similarly, the Gate Time Profiles for study area-2 (Figure 5.36 and Figure 5.37) and 3 (Figure 5.38 and Figure 5.39) are shown in Appendix-2. The samples of Fussel-Vesely Importance graph for LH21 and LH22 are shown in Figure 5.40 and Figure 5.41 (Appendix-2) for identification of basic cut sets/components/events contribution on top gate (system) failure. Similarly, the samples of Fussel-Vesely Importance graphs for study area-2 (Figure 5.42 and Figure 5.43) and 3 (Figure 5.44 and Figure 5.45) are shown in Appendix-2. An example of the results summary screenshot of LH21 of study area-1 is shown in Figure 5.46. Similarly, the screenshots of study area-2 (Figure 5.47) and 3 (Figure 5.48) are shown in Appendix-2.

From the computed results of FTA (Table 5.7) of study area-1, the maximum percentage of overall system availability (As), was observed for the machine LH29 (79.59%) and minimum for the machine LH24 (70.10%). Similarly, for study area-2 LHD2 (91.02%) was maximum, and LHD4 (84.22%) was minimum (Table 5.8, Appendix-2). For study area-3 availability of E4-LHD4 (88.18%) was maximum, and

E3-LHD3 (86.81%) was minimum (Table 5.9, Appendix-2). FTA is not only used to estimate the overall system availability percentage but, also used to determine the contribution of most influencing sub-systems/components/cut sets on the system failure. These sub-systems are known as “critical events” in the assembly of the system which are leading to failure of the top event (end gate). From the graphical analysis of fussell-vesely importance plot**,** it was observed that the components of the transmission, cabin, frame, steering, dump box, axle and bucket attachment are critical, leading to LHD machine failure. It is recommended that more concentration/ focus is necessary on these critical parts to minimize system failure. The computed results showed that the machines were not maintained appropriately. Unavailability of the machine in its working state and its in-effective utilization causes a harsh reduction in production levels. This can be improved by strict adherence to PM schedules, better organization of men and machinery, skilled operating crew and well-maintained equipment. The efficient working of the machine can be obtained by increasing the Available Machine Hours (AMhr) in a planned shift.

FTA is one of the most frequently used methodologies in reliability modeling along with Failure Mode Effect Analysis (FMEA) (Arabian-Hoseynabadi, H. et al. 2010) which supplement each other. FMEA is a well-recognized method for product and process industry applications, which is used to analyze the failure behavior of the parts/components whereas, the FTA approach aims to quantify the reliability and availability of a complex system. It is also used to identify the percentage of contribution of influencing factors such as cut sets, parts, and components, etc. on top gate (system) failure. The information provided by FTA is believed as useful data to engineers and end-users for formulating maintenance plans; to reduce the operational, and maintenance costs, and finally leading to lower overall production cost.

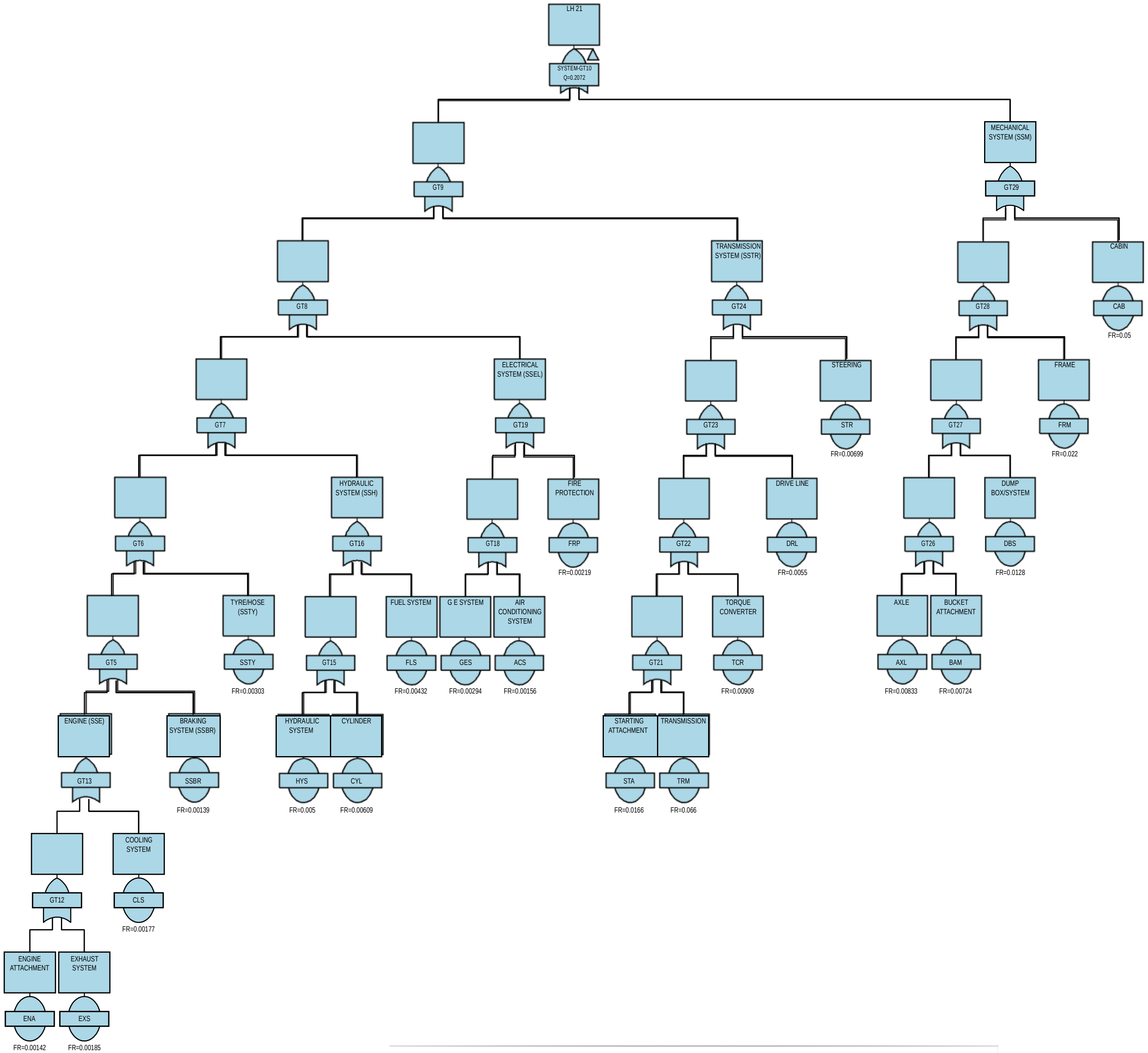


Figure 5.28 Fault Tree Diagram for LH21 of study area-1

Table 5.7 Percentage of overall system availability of LHDs for study area-1

Machine	MTBF (hours)	MTTR (hours)	Computed Availability (%)	Software Provided Availability (%)	Percentage of Variation (%)
LH21	32.65	7.82	80.67	79.28	1.39
LH22	15.71	4.43	78.00	77.35	1.35
LH24	21.99	9.45	69.99	70.10	0.11
LH25	33.36	13.89	70.60	71.71	1.11
LH26	25.26	8.53	74.75	72.53	2.22
LH27	45.46	13.64	76.92	78.94	2.22
LH28	23.70	7.26	76.55	76.73	0.18
LH29	35.13	9.93	77.96	79.51	1.55
LH30	117.88	31.23	79.05	77.49	1.56
LH31	60.43	17.31	77.73	77.73	0

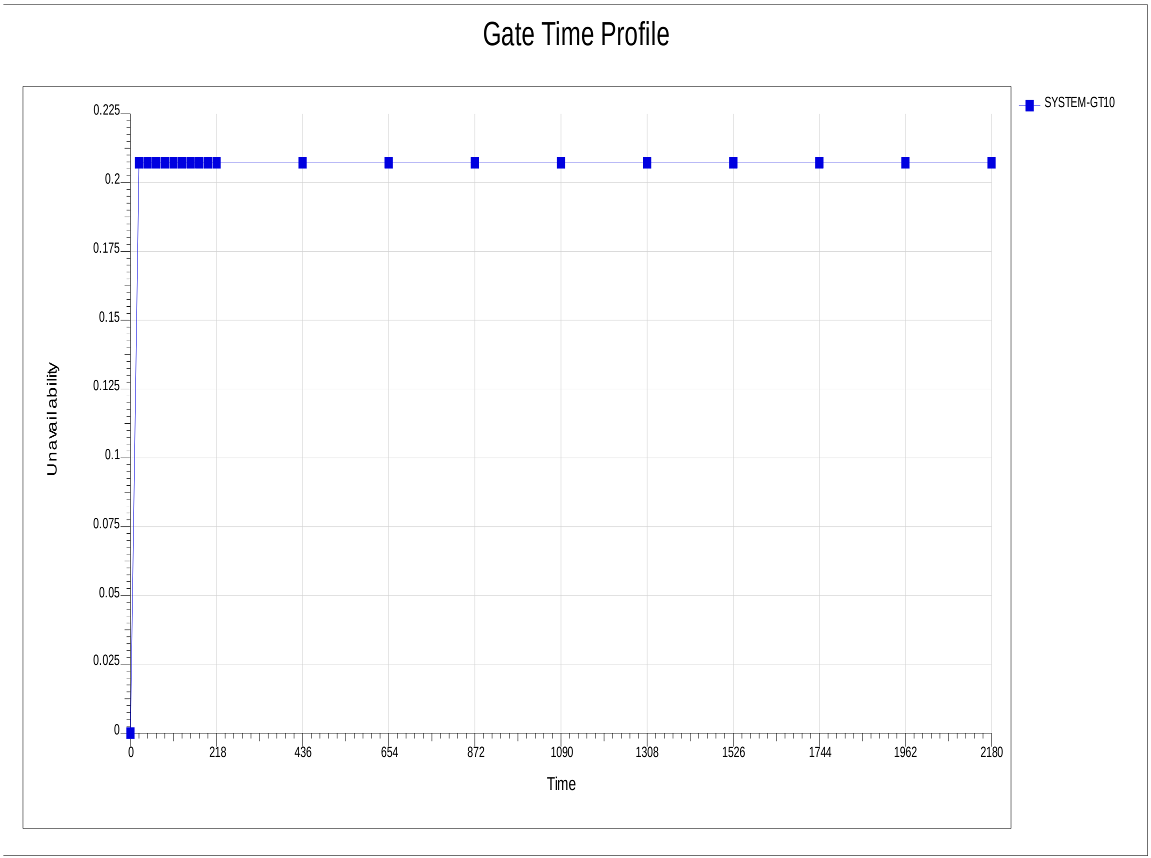


Figure 5.34 Gate time profile of unavailability of LH21 of study area-1

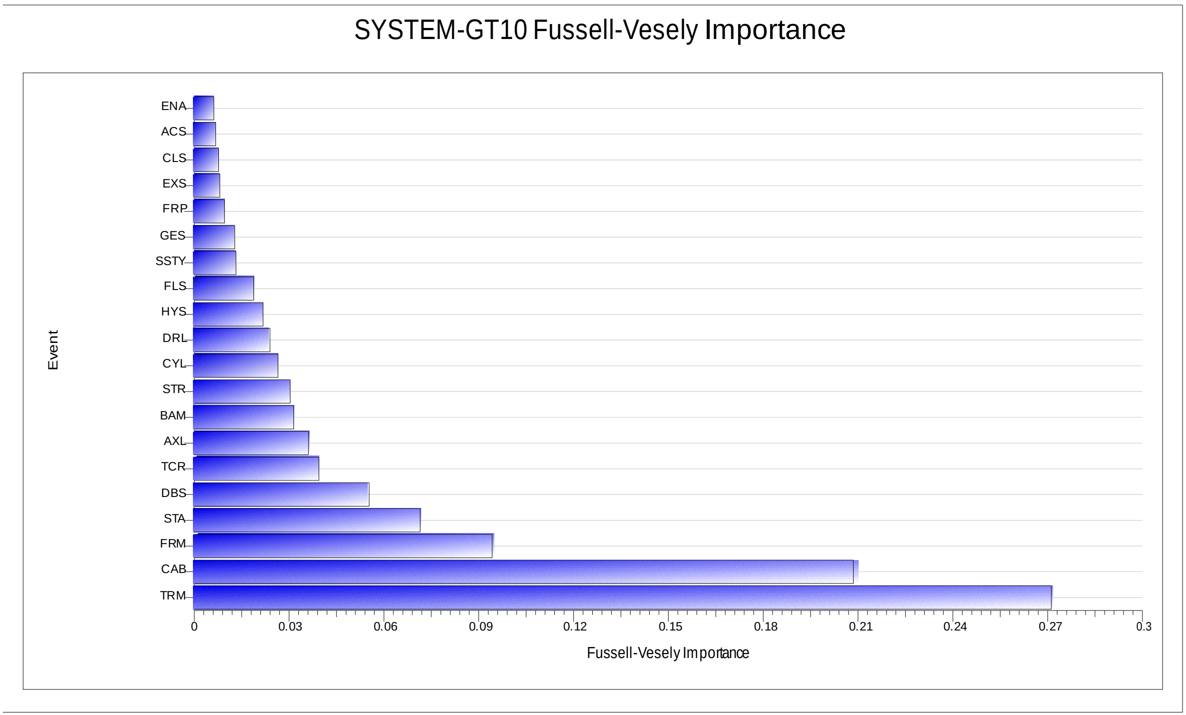


Figure 5.40 End gate Fussell-vesely importance of LH21 plot of study area-1

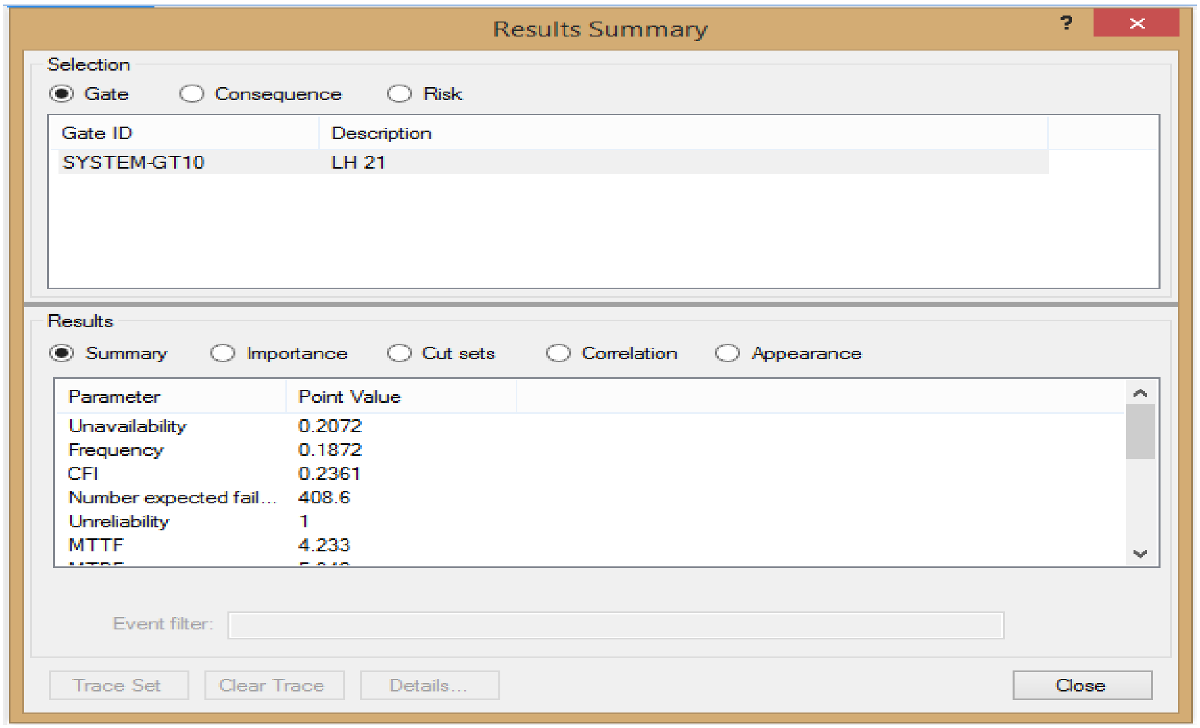


Figure 5.46 An example of results summary screenshot of LH21

5.3 FAILURE MODE AND EFFECT ANALYSIS (FMEA) FOR INVESTIGATION OF FAILURE BEHAVIOR OF THE SYSTEM

To improve the safety, reliability and robustness of equipment and tooling, there is a need for risk Analysis for sustainable operation of the projects. Failure mode and effect analysis (FMEA) is a widely used technique to identify the potential failure modes for measuring the reliability of a product or a process. FMEA is a methodology used to investigate the potential failures of systems occurring during the design and development phase. It helps to recommend suitable preventive actions to overcome the problems and to enhance the system reliability (Pravin. Gudale and Vinayak. Nayak 2014). FMEA is an engineering analysis done by a cross-functional team of subject matter experts that thoroughly analyses product designs or manufacturing processes, early in the product development process. Its objective is finding and correcting weaknesses before the product gets into the hands of customer. FMEA can be a guide for the development of a complete set of actions, that will reduce the risk associated activities up to the acceptable level in the process. From the perspective point of view the FMEA can be categorized into many types (Lazor. D. J. 1995):

- **Concept FMEA:** used to analyze the concepts for systems and subsystems in the early manufacturing stages.
- **Design FMEA:** used to analyze the products, high standard machines, components, standard production tools, etc. before the products are delivered into the market.
- **Process FMEA:** used to analyze the small scale machines or tools that allow for a customized selection of components, machine structure, bearings, coolants, etc.
- **Service FMEA:** used to analyze manufacturing and assembly processes and operational aspects of working machinery.

5.3.1 Conventional Failure Mode and Effect Analysis (FMEA)

The conventional Failure Mode and Effect Analysis (FMEA) approach is a pro-active quality tool for evaluating potential failure modes and their causes. It helps in prioritizing the failure modes and recommends corrective measures for the avoidance of catastrophic failures and improvement of the quality of the product. The conventional FMEA approach is a step-by-step process for the prioritization of different failures. The approach begins with the identification of all the paths through which failure can happen, called "potential failure modes". The potential failure mode identifies different factors by which the prioritization is obtained. The machine downtime (time for which the machine stops) identifies the Severity (S). The Occurrence (O) is defined as the probability of similar kind of failure that can happen within a specified time. Detection (D) is defined as the chances (easy, moderate or high) of identification of a failure mode. All these Severity, Occurrence and Detection factors are listed in different ranking**s** according to suitable standard nominations of 1 to 10 scale. Finally, Calculation of Risk Priority Number (RPN) is undertaken using the factors discussed. These numbers prioritize the potential failures for the given system.

In the FMEA application, possible failure modes, possible effects of these failure modes, prioritization of these failure modes and the corrective measures are identified with the help of a template in a data sheet. Initially**,** failure modes are identified. These are the ways or modes in which a subsystem/component/asset can fail. Further, the level of Severity, Occurrence and Detection are estimated to identify the hazard/risk of the failure mode. Normally, the level of risk can be measured by the computed metrics of 'Risk Priority Number (RPN)' (Dieter. G. 2000). The RPN value can be computed with the product of the Severity of the failure; the probability of its Occurrence; and the chance of Detection level of failure (Stamatis. D.H 2003). The rank 1 can be assigned for the highest value of RPN number of various failure modes.

5.3.2 The procedure of FMEA

Performing FMEA begins with the selection of a machine to be analyzed. The relationship between the machine and its working environment should be clearly understood to decide on the effects and reasons for potential failures. After the scope for FMEA has been decided, the plan of further investigation is as follows:

- Categorize the subsystems from the selected system/machine based on the failure type.
- Analyze the functioning of a component and its sub-components. Each function should be determined and the breakdown criteria of the function should be characterized entirely.
- Identify the breakdown modes of the element. For each breakdown mode, the accountable breakdown system and their occurrences are resolved.
- Develop control designs that recognize uncertainty systems, modes, and impacts. The viability of each arrangement is assessed by identification of the ranking.
- Assess the general hazards of a breakdown mode. The general hazard is estimated by the risk priority number (RPN), which can be calculated by multiplying the severity, occurrence and detection parameters. A high RPN indicates a high hazard/potential of that component for a breakdown. Restorative procedures have to be taken to decrease the hazard.
- Finally, the after-effects of FMEA are recorded utilizing an identical set-up.

The sequential procedure of present analysis with the application of FMEA is demonstrated as follows (Figure 5.49) (Arvanitoyannis, I. S. and Varzakas, T. H., 2009):

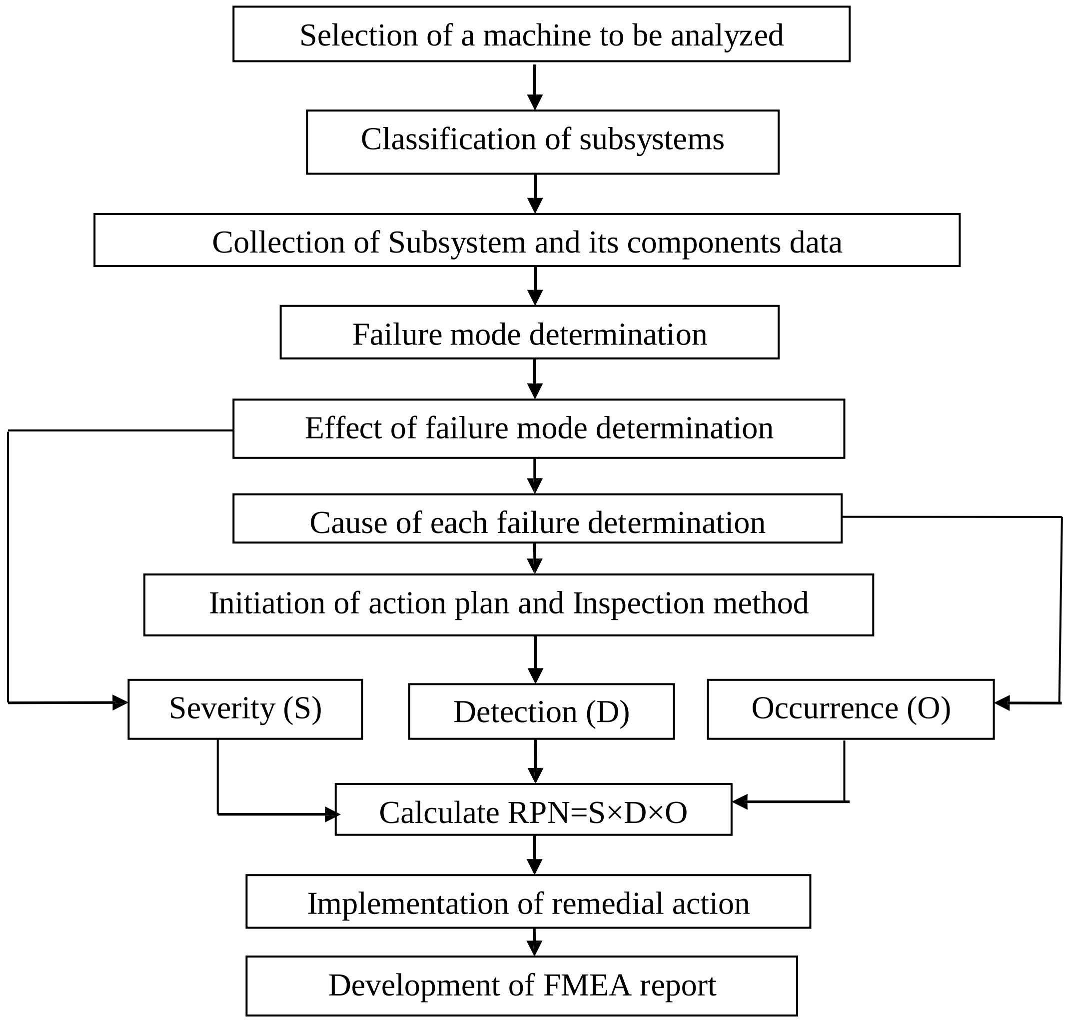


Figure 5.49 Flow chart for the sequential procedure of FMEA analysis

5.3.3 Potential Failure Modes and Effects

Potential Failure Mode is characterized as a system, sub-system or component which may fail before meeting the designed targets. The primary potential breakdown may trigger the occurrence of secondary failure (i.e., breakdown of the lower-level component) due to a lack of spontaneous attention of the maintenance crew to repair or replace the failed part. Every potential breakdown mode for the specific component and its function have to be recorded. For instance of time, the same kind of failure may or may not happen for more than one time.

"Imminent Failure Effect" is characterized as the impact of the breakdown mode and should be based on the evaluation or analyses of the system response following failure. It may have physical or health and safety consequences and it needs to be clearly stated that it could impact safety or non-cooperation to the system (Maiti, J. 2005 and Chin. K. S. 2008).

5.3.4 Risk Indexed Parameters

The FMEA technique is not only used to identify the potential breakdown mode but also used to prioritize the failure modes based on an assessment of risk indexed parameters. In general, prioritization of critical failure can be determined through the calculation of Risk Priority Number (RPN) value. This can be achieved by multiplying the indices of O, S and D of each failure.

- **Severity (S)**

The "Severity (S)" assesses the criticality of the impact of the potential hazard occurring. The S score is assessed against the impact of the effect brought about by the failure mode and is shown in Table 5.10.

Table 5.10 Severity criteria for FMEA (Balaraju Jakkula et al. 2019)

The Severity of a Failure		
Sl. No	**Severity Description**	**Risk Scale/Rank**
1	No Effect	1
2	Very Minor Effect	2
3	Minor Effect	3
4	Very Low Effect	4
5	Low Effect	5
6	Moderate Effect	6
7	High Effect	7
8	Very High Effect	8
9	Hazardous –Warning	9
10	Hazardous No Warning	10

- **Occurrence (O)**

Occurrence estimates the quantity of a potential risk(s) that will occur for a given circumstance or a framework. The probability of Occurrence rate/rank of a failure mode can be taken against the number of times the same failure that can happen (Table 5.11).

Table 5.11 Probability of occurrence criteria for FMEA (Balaraju Jakkula et al. 2019)

The occurrence of a Failure		
Probability of Occurrence	**Failure**	**Rate/Rank**
Remotely Occurrence	1E-06	1
Very Less Chance of Occurrence	1E-05	2
Less Chance of Occurrence	0.0001	3
Moderate Probability: 1 in 2000	0.0005	4
Moderate Probability: 1 in 400	0.0025	5
Moderate Probability: 1 in 80	0.0125	6
High Chance of Occurrence: 1 in 20	0.05	7
High Chance of Occurrence: 1 in 8	0.125	8
Very High Chance of Occurrence: 1in 3	0.25	9
Very High Chance of Occurrence: 1 in 2	0.5	10

- **Detection (D)**

"Detection (D)" is the likelihood of the breakdown being identified before the effect of the breakdown on the procedure or framework being evaluated. The D score is appraised against the capacity to recognize the result of the breakdown mode and is shown in Table 5.12.

Table 5.12 Detection criteria for FMEA (Balaraju Jakkula et al. 2019)

Detection of a failure		
Probability of Detection	**Detection Scale**	**Detection Rate/Rank**
Almost Certain	1	1
Very High	0.5	2
High	0.25	3
Moderately High	0.125	4
Moderate	0.05	5
Low	0.0125	6
Very Low	0.0025	7
Remote	0.0005	8
Very remote	0.0001	9
Absolute Uncertainty	0	10

- **Risk Priority Number (RPN)**

RPN is the result of the rating of three data sources (Severity, Occurrence and Detection). This can be utilized at the time of risk assessment of failure, and the metric of RPN is computed from Equation 5.65, as given below:

$$\text{RPN}=\text{Severity (S)} \times \text{Occurrence (O)} \times \text{Detection (D)} \qquad (5.65)$$

RPN gives direction to ranking the potential breakdowns and identifying the recommended actions for outlines or process changes which would reduce Severity or Occurrence. Failure modes with higher RPN values are assumed to be more hazardous and there is an urgent requirement to resolve them than those with lower RPN values (Wang. L. X. 2008).

FMEA uses O and D probability criteria in conjunction with S criteria to develop the RPN for prioritization of corrective actions (Roberto. Bubbico. et al. 2004). In this investigation, risk analysis has been carried out for (10+5+5) 20 numbers of LHDs deployed in three different study areas. Breakdown data for 24 months were taken into consideration for the analysis. Some of the potential failures of the LHD system are provided in Figure 5.50 and a fishbone diagram for root Cause Analysis (RCA) of the LHD is shown in Figure 5.51. Ranking criteria of S, O and D were chosen appropriately by the type of failure mode by analyzing the breakdown reports. Each failure mode is expressed in the serial order with a letter 'F'. The method of conventional FMEA has been adopted in this analysis. In this FMEA investigation, RPN values were computed with the product of S, O and D metrics. The ranking criteria of S, O, and D of each failure mode was determined (Table 5.13) in the FMEA worksheet of LHDs of study area-1. The determined ranking criteria of study area-2 (Table 5.14), and study area-3 (Table 5.15) are given in Appendix-2. After the estimation of the RPN values of each failure mode, necessary repair or replacement actions were suggested to control the occurrence of frequent failures and resumption of the operation of the equipment and production process. Based on the recommended action ranking criteria of S, O, and D of each failure mode was determined for a second time to estimate the value of the action results of RPN. The estimated values of RPN metrics along with the action results of RPN are given in Table 5.16. Similarly, the estimated results of RPN along with action results RPN for study area-2 (Table 5.17), and 3 (Table 5.18) are given in Appendix-2. For better understanding, the computed RPN values along with action results of RPN of study area-1 are shown in Figure 5.52 (a), and (b). Similarly, these RPN, and action RPN results of study are-2 (Figure 5.53 (a) and (b)), and study area-3 (Figure 5.54 (a) and (b)) are shown in Appendix-2. The percentage variation of computed RPN values with action results of

RPN of study area-1 is shown in Figure 5.55. Similarly, the percentage variation for study area-2 (Figure 5.56) and study area-3 (Figure 5.57) are shown in Appendix-2.

From the results (Table 5.16) of the conventional FMEA approach in respect of study area-1, it was noticed that the highest RPN values were obtained for SSTy (F2-128), SSH (F5-144), and SSE (F9-168). The corresponding action results of RPN for priority rankings for various failure modes are identified due to remedial action F2-72, F5-72, and F9-80. Similarly, the highest RPN values were obtained for study area-2 in respect of SSE (F1-144, F3-168, and F4-147), SSEl (F5-135, F6-144, F7-180, and F8-162), SSBr (F16-144, and F17-180), and SSTr (F18-160, and F19-162). The corresponding action results of RPN with respect to priority rankings for various failure modes are identified as F1-72, F3-80, F4-105, F5-75, F6-72, F7-90, F8-105, F16-72, F17-96, F18-120, and F19-126. The highest RPN values were obtained for study area-3 in respect of SSE (F1-180, and F5-162), SSTr (F16-160, and F17-162), SSH (F22-168), and SSM (F28-162). The corresponding action results of RPN for priority rankings for various failure modes are identified as F1-60, F5-90, F16-90, F17-126, F22-96, and F28-126. The RPN values of sub-systems increased due to the highest seriousness in severity and probability of occurrence of failures in a considered time. The RPN will provide "guidance for prioritization" of probable failure modes, to minimize the level of severity and failure occurrence. It will also be useful to identify or recommend the necessary actions for design or process modification. If the RPN value is high, then the effect of failure mode is more critical, which reduces the life of the equipment, and the corresponding reduction of mine production. This can be improved by conducting the scheduled PM within time intervals recommended for the equipment, by giving proper training and awareness on each component/part to the maintenance and operational personnel. In contrast to FTA, Failure Mode Effect Analysis (FMEA) provides complete information on failure behaviour through root cause analysis. This analysis is helpful to determine the potential causes of the failure, starting with the highest severity rating. The FMEA datasheet is used as a historical guideline to make future predictions about the occurrence of early life failures, to take the corrective actions to mitigate the failure occurrence and to establish the risk priorities of various failures for design improvement of components.


Replacement of Bucket Attachment (Boom)


Hose Failure


Electric Control Failure


Tyre Failure/Puncture


Bucket Attachment System Failure


Steering Direction Main Spool


Lift Cylinderod Broken


Engine Supporting Block Broken

Figure 5.50 Some potential failed parts of an LHD system

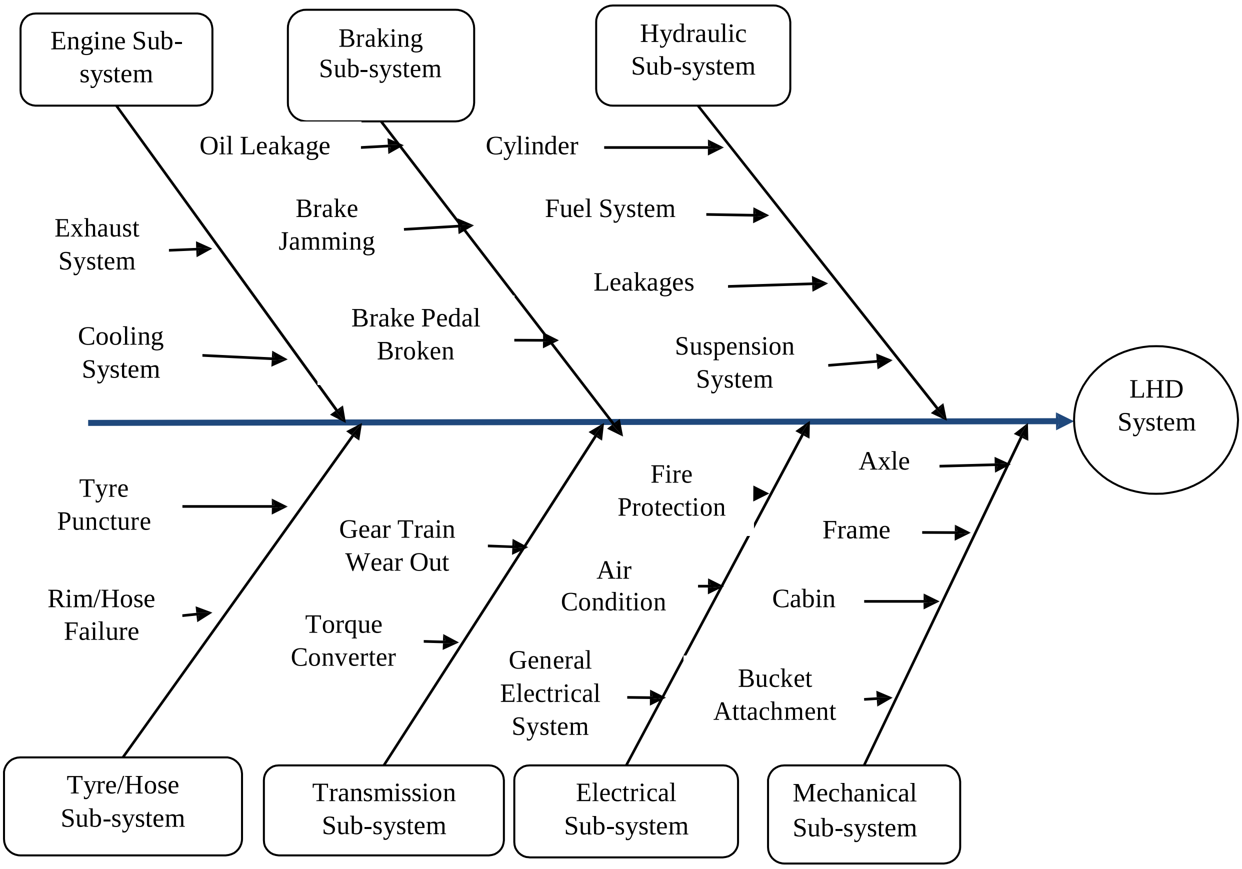


Figure 5.51 Fishbone diagram for the root cause analysis (RCA) of the LHD

Table 5.13 FMEA worksheet (process FMEA) of LHDs of study area-1

Sub-system	Potential Failure Mode	Effects Description	Potential Cause (s)	Risk Index				Recommended Actions	Actions are taken	Action results			
				S	O	D	RPN			S	O	D	RP N
SSBr	Brake pedal broken (F1)	Prone to accidents	Wear and tear, lubrication and lack of daily inspection	2	6	3	36	Brake system needs to be cleaned every 1000 hours.	Repair action of components control the accidents	2	3	4	24
SSTy	Tyre punctures (F2)	The machine was stopped for repair	Poor underfoot conditions, overloading, improper inflation	8	8	2	128	Remove and send toe-buttoning agencies	Repair action help to continue the operation	6	4	3	72
	Tyre burst (F3)	The machine was stopped for repair	Incorrect fitment, excessive torque, concerning or spin, defective conditions	7	8	1	56	Remove the tyre and replace with a new one	Replacement action should help to restore machine in its working place	5	6	1	30
SSH	Directional solenoid connector spool damage (F4)	Flush entire hydraulic system post failure of any component	Metal particles trapped in spool	2	9	2	36	Hydraulic oil needs to be cleaned & flushed every 1500hours	Cleaning action of hydraulic oil should help to control the failures	2	6	2	24

	Cylinder bearing damaged (F5)	The hydraulic system will be damaged	Wear and tear	3	8	6	144	Check for greasing and if require d replace with a new one	Replacement action minimize the failure of the hydraulic system	3	6	4	72
	Lift cylinder piston rod eye broken and it got bend during lowering the boom (F6)	Poor operating practices and Lack of proper maintenance	Lift cylinder damaged and hydraulic oil leakage	2	8	6	96	Do not connect the internal components of one cylinder to another and check & correct boom stopper	Recommended action may helps to avoid the early life failure of the lift cylinder	2	6	4	48
	Cracks on the cylinder (F7)	Cylinder damage	Lubrication, wear and tear	2	4	6	48	Training to be conducted for maintenance crew about Control of Contamination	Provision of sufficient amount of lubrication should reduce the cylinder damage	2	4	4	32
SSE	Engine mounting bracket (Rear Supporting Blocks) broken (F8)	Misalignment with adjacent components led to breakage	Continuous impact and stress concentrated on the weak portion of the supporting block	7	4	2	56	Replace with a modified design bracket	Replacement action components should reduce the impact on week portions	4	5	2	40

	Steering function not working (F9)	Machine directions are not possible to control	Internal failure of the directional spool due to aging	4	6	7	168	Replace steering main valve	Replacement action continue the functioning of the steering	4	5	4	80
SSEl	Cable drum sprocket, chain fail (F10)	The machine is not operable	Lack of greasing, wear and tear	8	3	4	96	Greasing should be done daily for bearings	Daily basis provision of greasing help to machine operable	6	3	2	36
	Cable reel fail (F11)	The machine is not operable	Improper maintenance, aging factor	8	2	4	94	Remove and replace with a new one	Replacement action help to the machine will operable	5	2	3	30
SSTr	Transmission oil leakage (F12)	The engine dropped slightly from its mounting position	Breakage of torque convert the reregulating valve	3	8	3	72	Replace with a new regulating valve	Replacement action of torque converter regulating valve should help to keep the machine to its mounting position	2	6	4	48

SSM	Swing lever eye has broken (F13)	The machine is not operable	The machine was without greasing for the last 8 consecutive shifts and machine is regularly operated by operators	5	4	1	20	Operator refresher training to be conducted and greasing of the machine must be done	Necessary managerial action should help to machine operable	3	4	4	48
	Boom broken (F14)	Production stoppages	Overloading, Lifting cylinder breakage and poor welding at the joints	9	3	2	54	Remove and replace with a strengthened one	Replacement action of boom helps to continue the generation	6	3	2	36
	Bucket broke (F15)	Production stoppages	Poor welding at the joints	9	4	2	72	To be welded at the required sections	Repair action helps to continue the generation	6	4	2	48
	Knuckle joint's swing leaver eye broken (F16)	The machine is not operable	Due to rough operation and lack of lubrication	8	3	2	48	Operator refresher training and greasing of the machine should done	Correct operating practices and proper maintenance actions helps to continue the machine operation	6	3	2	36

Table 5.16 Computed risk indexed parameters and RPN metrics of study area-1

Sub-system	Failure Type	Risk Indexed Parameters			RPN	Action Results of Risk Indexed Parameters			Action Results of RPN
		(S)	(O)	(D)		(S)	(O)	(D)	
SSBr	F1	2	6	3	36	2	3	4	24
SSTy	F2	8	8	2	128	6	4	3	72
	F3	7	8	1	56	5	6	1	30
SSH	F4	2	9	2	36	2	6	2	24
	F5	3	8	6	144	3	6	4	72
	F6	2	8	6	96	2	6	4	48
	F7	2	4	6	48	2	4	4	32
SSE	F8	7	4	2	56	4	5	2	40
	F9	4	6	7	168	4	5	4	80
SSEl	F10	8	3	4	96	6	3	2	36
	F11	8	2	4	64	5	2	3	30
SSTr	F12	3	8	3	72	2	6	4	48
SSM	F13	5	4	1	20	4	4	1	16
	F14	9	3	2	54	6	3	2	36
	F15	9	4	2	72	6	4	2	48
	F16	8	3	2	48	6	3	2	36

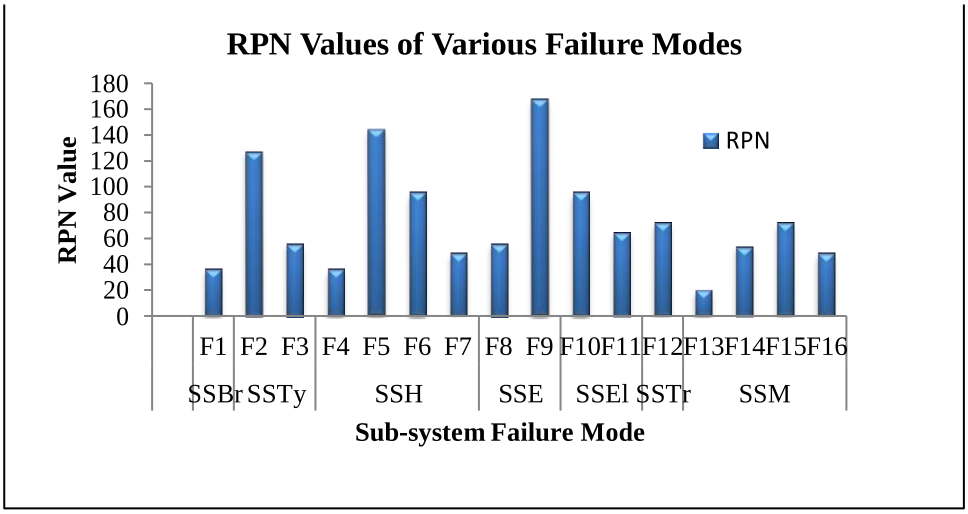


Figure 5.52 (a) RPN values of various failure modes of study area-1

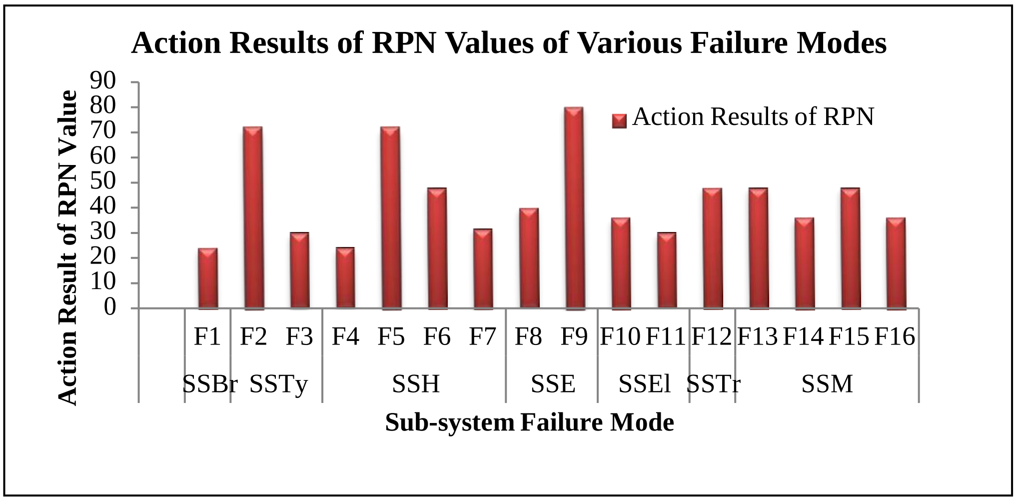


Figure 5.52 (b) Action result RPN values of various failure modes of study area-1

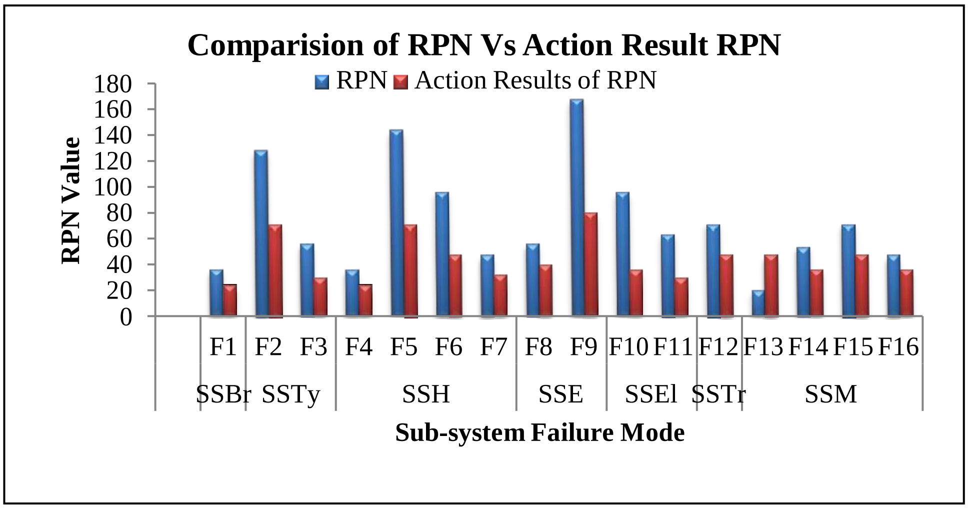


Figure 5.55 Percentage variation of RPN with action RPN results of study area-1

Data validation is the corresponding procedure after estimating the performance characteristics such as reliability, availability and maintainability, etc of an equipment. Data validation is intended to provide certain well-defined guarantees and consistency of data in an application or automated system. To solve the complex problems like an estimation of the performance of the equipment using analytical and statistical approaches will take a bit more time as compared with software-based approaches. Soft tool computing techniques such as Artificial Neural Network (ANN), Fuzzy analysis has been utilized in the next chapter to validated the performance characteristics of a machine.

CHAPTER-6

VALIDATION OF LHD PERFORMANCE CHARACTERISTICS WITH MATLAB PREDICTIONS

Analytical and statistical approaches will take longer time to solve complex problems such as performance estimations as compared with software-based approaches. Nowadays, soft computing techniques have caught the attention of researchers for resolving a variety of non-linear problems, that need large computations. The application of Soft Computing (SC) techniques in the mining industry is fairly extensive and covers a considerable number of applications. The principal SC technologies can be categorized as fuzzy algorithms, neural networks, supporting vector machines, evolutionary communication, machine learning, and probabilistic reasoning (Hartman. H and Mutmansky. J. 2002 and Zadeh. L. A. 1994). This chapter validates the computed results of RAM parameters such as availability, reliability, and preventive maintenance with MATLAB based ANN predictions. It also validates the estimated values of RPN in conventional FMEA with MATLAB based Fuzzy-FMEA analysis.

6.1 ARTIFICIAL NEURAL NETWORK (ANN) MODELLING

Nowadays, soft computing techniques have captured the attention of researchers for resolving a variety of non-linear challenges connected with environmental and system operation related problems. In general, most of the conventional analysis approaches cannot be resolved without the utilization of fundamental equations, traditional correlations, or developing distinctive tasks from investigational records through trial and error (Kapageridis. I. 2002). Artificial neural network (ANN) technique has been applied for different kinds of difficult issues, which are not comprehended by regular strategy in different fields. The ANN approach is a less time-consuming process for resolving complex problems with precise accuracy (Ghobadian. B. et al. 2009). ANN can model both linear and non-linear systems without considering any kind of assumptions (Mohd, Noor. C. W. et al. 2015). Hence, this tool has been becoming increasingly popular in various Engineering fields.

In the ‘90s the mining industry was introduced to several ANN-based systems, some of them finding their way to a fully commercialized product (Kapageridis, I. 1999). Later on universities, and research institutes around the world have started working on a wide variety of research applications (Kapageridis, I. 2002). The application of Soft Computing (SC) techniques in the mining industry is fairly extensive and covers a considerable number of applications (Yama. Lineberry. 1999). McCulloch and Pitts, 1943 have introduced an initial model of an artificial neural network (ANN), which was recognized as the first study of artificial intelligence. Since then, a significant amount of ANN-related research has been conducted (McCulloch. W. S and Pitts. W 1943 and J. Hall. A and Daneshmend. L. K. 2003). The artificial neural network (ANN) has been widely touted as solving many forecasting and maintenance decision modeling problems of machinery (Singh.T. 2004). The ANN tool is used to predict the functions of shovel-dumper performance results using biases and weights of the network to minimize the error between them for interpolation with the computed results (Mousa. Mohammadi. 2015). ANN method, for example, helps the decision-makers to determine the best time economically to replace an old machine with a new one; thus, it can be extended to more general applications in the mining industry (Hussan. Al-Chalab et al. 2014). The present study is focused on the application of the ANN technique for estimation of the performance of mining equipment. It is an intricate handling process that can predict the outputs based on the nature and kind of given inputs. The predictive ability of ANN results from the training on experimental data, and then validation by independent data. To predict the various output responses**,** this ANN technique can accommodate multiple input variables. This technique contains three numbers of layers: such as information layer for input, shrouded layer for mixing and yield layer for output. An example of the feed-forward system is given in Figure 6.1.

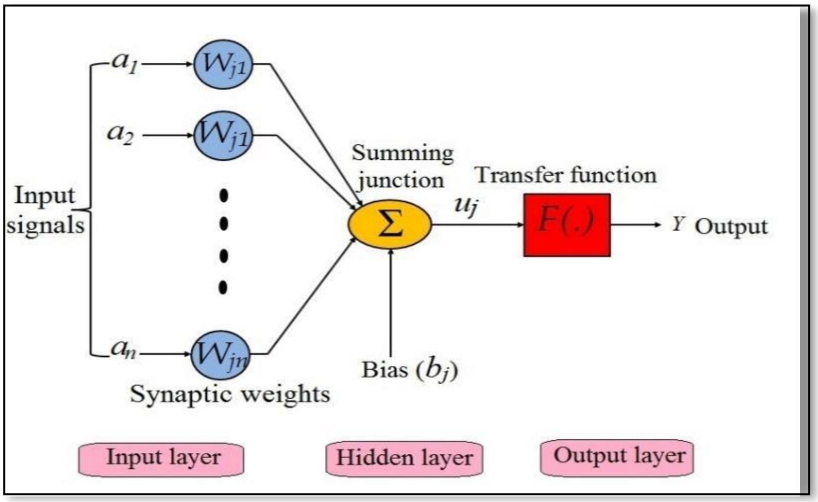


Figure 6.1 Basic structure of the ANN model

Progress of the ANN technique in Automotive Engineering has progressed at a very impressive rate in recent years. Some researchers (Hartman. H and Mutmansky. J. 2002 and Zadeh. L. A. 1994) used ANN to predict mechanical performance characteristics. The present research work intends to investigate the applicability of the ANN method to predict LHD machine performance characteristics. In this study, the computed values of LHD machine performance characteristics were validated with the MATLAB based ANN predicted results. The availability, reliability and PM parameters of LHDs were modelled using ANN tool (Figure 6.2, Figure 6.3, and Figure 6.4). To estimate the availability of the system, two numbers of parameters such as MTBF and MTTR were given as input. Whereas in the case of prediction of reliability, four numbers of parameters like MTBF, scale parameter (η), shape parameter (β) and location parameter (γ) were given as input. Similarly, for prediction of PM, percentage of reliability (R), scale parameter (η), shape parameter (β) and location parameter (γ) were given as input. These three predicted values (availability, reliability and PM) from the output layer of the ANN model were compared with the computed values.

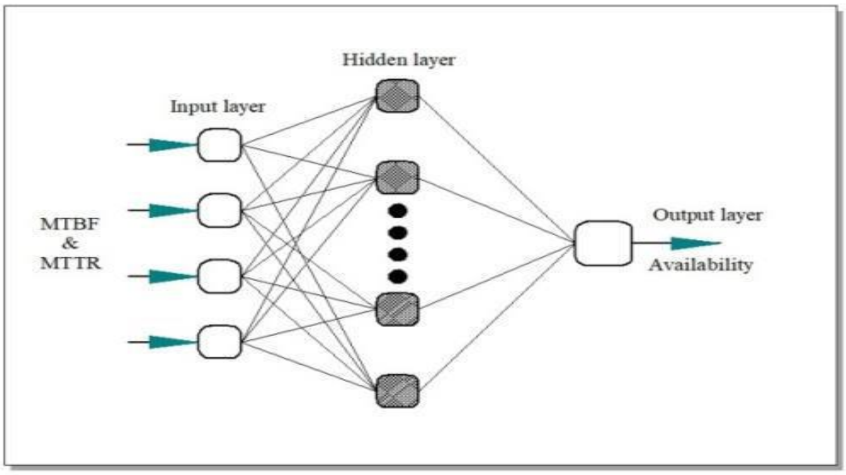


Figure 6.2 ANN model for availability

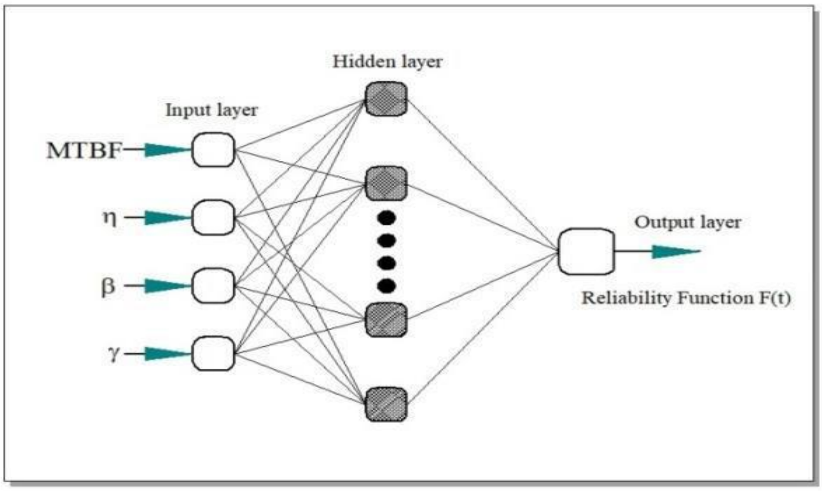


Figure 6.3 ANN model for reliability

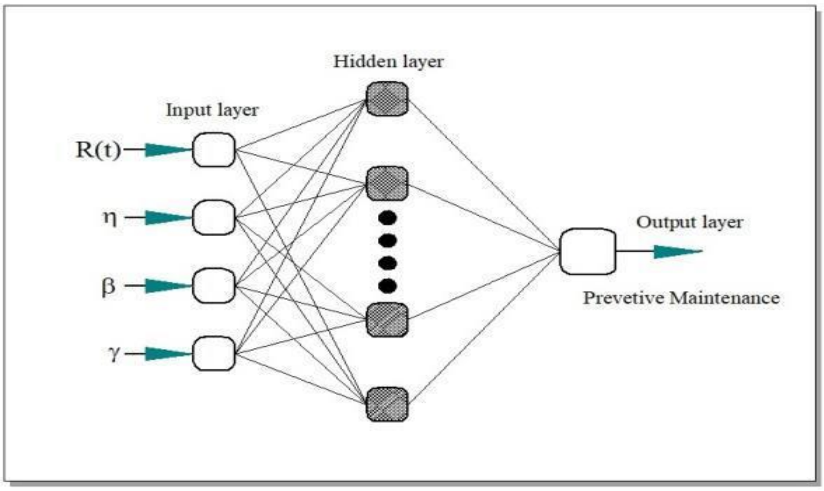


Figure 6.4 ANN model for PM

6.1.1 Development of ANN Simulation Model for Availability

ANN model of availability was developed by utilizing the MTBF and MTTR metrics. TRAINLM learning function has been used for training purposes. After selecting the training function, the learning function was selected as LEARNGDM (Gradient Descent with momentum weight and bias learning function). TANSIG transfer function was selected for the hidden layer and linear function (PURELIN) for the output layer. In study area-1, the model was tested by varying the number of neurons from 3 to 10 and trained up to 1000 iterations for obtaining the best optimum results. The selection of the optimum value of R^2 was done based on root Mean Square Error (RMSE) (Equation 6.1) value. From the obtained results it was noticed that R^2 (0.9960) was optimum at 0.4696 (RMSE) for LM-8 (Table 6.1). The Training performance of the availability of various neurons is given in Table 6.2. The developed optimal availability ANN model of LM-8 for study area-1 is shown in Figure 6.5. Similarly, in the study area-2, the model was tested by varying the number of neurons from 4 to 10 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9974) was optimum at 0.4979 (RMSE) for LM-8 (Table 6.3). The Training performance of the availability of various neurons is given in Table 6.4. The developed optimal availability ANN model of LM-8 for study area-2 is shown in Figure 6.6. In the same way, for study area-3, the model was tested by varying the number of neurons from 4 to 10 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9939) was optimum at 0.4018 (RMSE) for LM-4 (Table 6.5). The Training performance of the availability of various neurons is given in Table 6.6. The developed optimal availability ANN model of LM-4 for study area-3 is shown in Figure 6.7. For these, predicted values of the optimum R^2 of study area-1, 2, and 3 are recorded for validation purposes.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y - y')^2}{n}} \qquad (6.1)$$

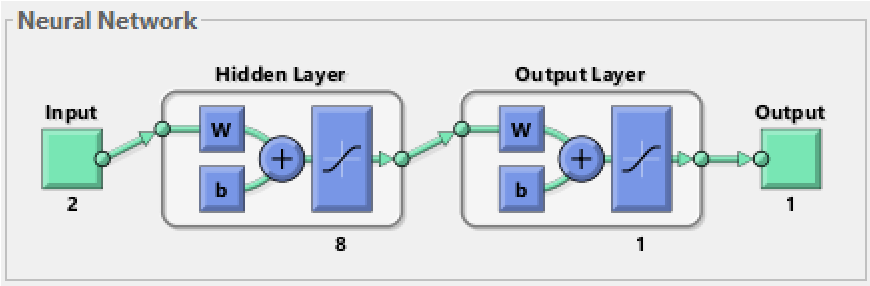


Figure 6.5 Developed ANN availability model of neuron-8 for study area-1

Table 6.1 Training performance of availability for various neurons for study area-1

Sl. No.	Number of Neurons	R^2	RMSE
1	3	0.9874	0.54192
2	4	0.9764	2.0101
3	5	0.7453	2.4586
4	6	0.9867	2.5152
5	7	0.9864	0.5840
6	**8**	**0.9960**	**0.4696**
7	9	0.9844	2.4351
8	10	0.9663	2.0010

Table 6.2 Predicted values of availability from ANN model for study area-1

Sl. No.	Machine	MTBF (hours)	MTTR (hours)	Availability (%)
1	LH21	5.34	1.10	79.13
2	LH22	3.65	1.20	76.92
3	LH24	3.05	1.28	70.96
4	LH25	3.00	1.00	72.5
5	LH26	3.21	1.25	72.88
6	LH27	3.83	1.17	78.85
7	LH28	3.58	1.20	76.62
8	LH29	3.91	1.17	79.51
9	LH30	3.90	1.17	79.51
10	LH31	3.72	1.20	77.17

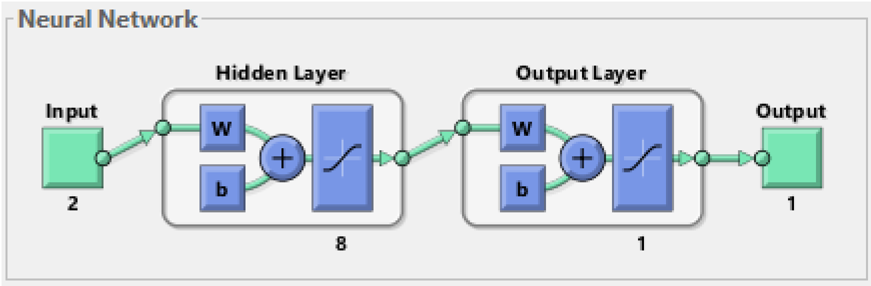


Figure 6.6 Developed ANN availability model of neuron-8 for study area-2

Table 6.3 Training performance of availability for various neurons for study area-2

Sl. No.	Number of Neurons	R^2	RMSE
1	4	0.7239	1.2012
2	5	0.8117	1.0414
3	6	0.9718	0.5101
4	7	0.9835	0.5800
5	**8**	**0.9974**	**0.4979**
6	9	0.9812	0.5814
7	10	0.9772	0.5002

Table 6.4 Predicted values of availability from ANN model for study area-2

Sl. No.	Machine	MTBF (hours)	MTTR (hours)	Availability (%)
1	LHD1	101.47	10.7	91.50
2	LHD2	112.7	16.07	92.47
3	LHD3	459.45	234.5	97.7
4	LHD4	190.56	18.51	86.17
5	LHD5	485.81	45.54	97.50

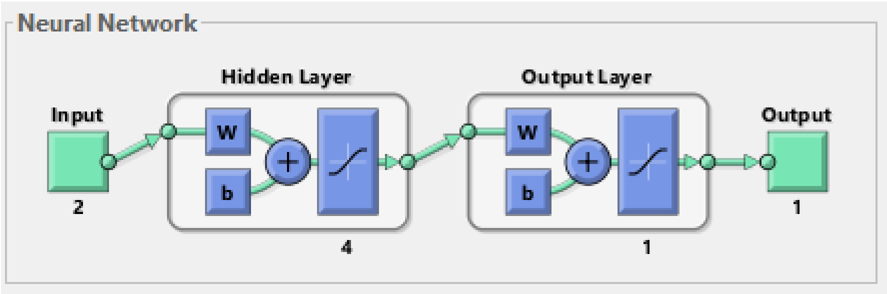


Figure 6.7 Developed ANN availability model of neuron-4 for study area-3

Table 6.5 Training performance of availability for various neurons for study area-3

Sl. No.	Number of Neurons	R^2	RMSE
1	2	0.9018	0.8014
2	3	0.9887	0.5811
3	**4**	**0.9939**	**0.4018**
4	5	0.9898	0.5916
5	6	0.8367	1.0415
6	7	0.8128	1.0415
7	8	0.9766	1.0619
8	9	0.9409	0.5010
9	10	0.7429	0.8134

Table 6.6 Predicted values of availability from ANN model for study area-3

Sl.No.	Machine	MTBF (hours)	MTTR (hours)	Availability (%)
1	E1-LHD1	72.68	16.59	89.75
2	E2-LHD2	64.35	19.24	68.99
3	E3-LHD3	85.48	14.74	88.73
4	E5-LHD5	84.58	11.12	87.22
5	E6-LHD6	87.38	13.27	88.60

6.1.2 Validation of the Computed Availability Results with ANN Predicted Results

In ANN modelling, 70% of the data must be taken for training and the remaining 30% is for testing purpose from the total data. In the present investigation, 80 data sets were used to perform the ANN analysis, out of which 56 data sets were used for the training set to adjust the weights of the input parameters, i.e., MTBF and MTTR. The remaining 24 data sets are used to measure the accuracy of the model, which gives the realistic estimate of the performance of the model on completely unseen data, and to confirm the actual predictive power of the network. The developed ANN simulation model of availability was optimized at neuron number-8 (2-8-1) for study areas 1, and 2, and the developed model was optimized for study area-3 at neuron number-4 (2-4-1). The predicted values of availability for study area-1 (Table 6.2), 2 (Table 6.4) and 3 (Table 6.6) were recorded corresponding to the optimized neurons of developed models for validation purpose. The computed availability results were validated with the predicted values for both study area-1 (Table 6.7), 2 (Table 6.8) and 3 (Table 6.9).

Table 6.7 Validation of predicted availability ANN results of study area-1

Sl.No.	**Machine**	**Computed Availability (%)**	**Predicted ANN Availability (%)**	**Percentage Error (%)**
1	LH21	80.67	79.13	0.00
2	LH22	78.00	76.92	0.54
3	LH24	69.99	70.96	-0.20
4	LH25	78.29	72.5	0.02
5	LH26	74.75	72.88	0.00
6	LH27	76.92	78.85	-0.70
7	LH28	76.55	76.62	-0.45
8	LH29	77.96	79.51	-0.31
9	LH30	79.05	79.51	0.86
10	LH31	77.73	77.17	-0.26

Table 6.8 Validation of predicted availability ANN results of study area-2

Sl.No.	Machine	Computed Availability (%)	Predicted ANN Availability (%)	Percentage Error (%)
1	LHD1	91.53	91.50	0.01
2	LHD2	92.39	92.47	0.98
3	LHD3	97.70	97.7	9.94
4	LHD4	85.90	86.17	-5.21
5	LHD5	97.12	97.50	0.05

Table 6.9 Validation of predicted availability ANN results of study area-3

Sl.No.	Machine	Computed Availability (%)	Predicted ANN Availability (%)	Percentage Error (%)
1	E1-LHD1	84.94	89.75	0.13
2	E2-LHD2	69.48	68.99	0.01
3	E3-LHD3	87.45	88.73	-0.08
4	E5-LHD5	88.82	87.22	-0.10
5	E6-LHD6	87.42	88.60	-0.00

In order to obtain a better understanding of the experimental and predicted ANN availability values, the error for the training and testing data sets has been drawn and is shown in Figures 6.8 (study area-1), 6.10 (study area-2) and 6.12 (study area-3). From the Figure 6.8 of study area-1, minimum error value (-0.70%) was noticed for LH27 and the maximum error value (0.86%) was noticed for LH30. Similarly, from Figure 6.10 of study area-2, minimum error value (-5.21%) was noticed for LHD4 and the maximum error value (0.86%) was noticed for LHD3. Figure 6.12 of study area-3, minimum error value (-0.10%) was noticed for E1-LHD1 and the maximum error value (0.13%) was noticed for E5-LHD5. Hence, the maximum error is within the limit (less than 10%).

The comparison of predicted results with computed availability values for study area-1, 2 and 3 are shown in Figure 6.9, Figure 6.11 and Figure 6.13 respectively. These figures shows that the predicted results were found to be closer to the computed values. Hence, it was concluded that the neural network is an appropriate model for the developed network models.

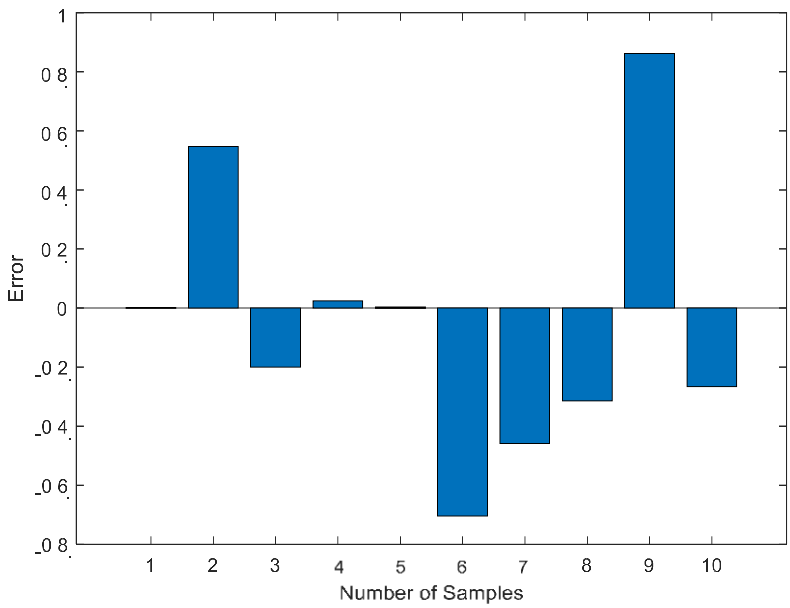


Figure 6.8 Error graph of availability data sets (2-8-1) of study area-1

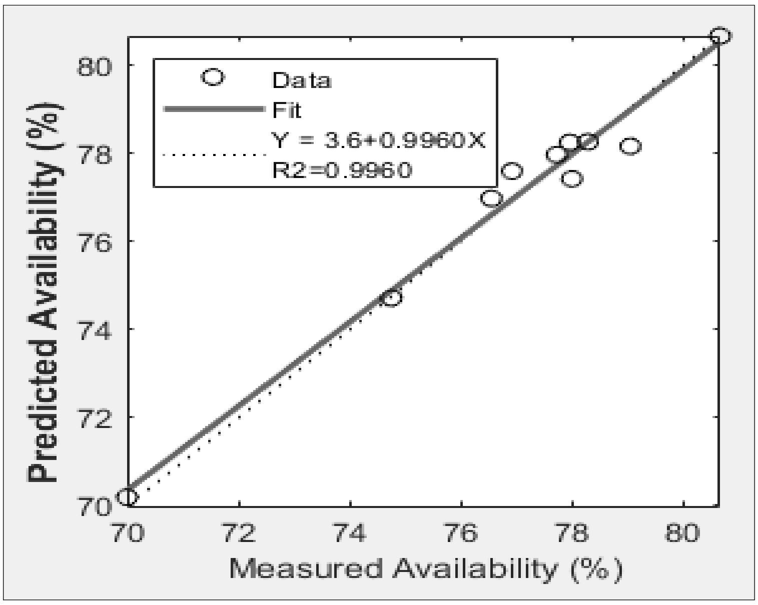


Figure 6.9 Predicted and computed ANN availability results of the Training data sets of study area-1

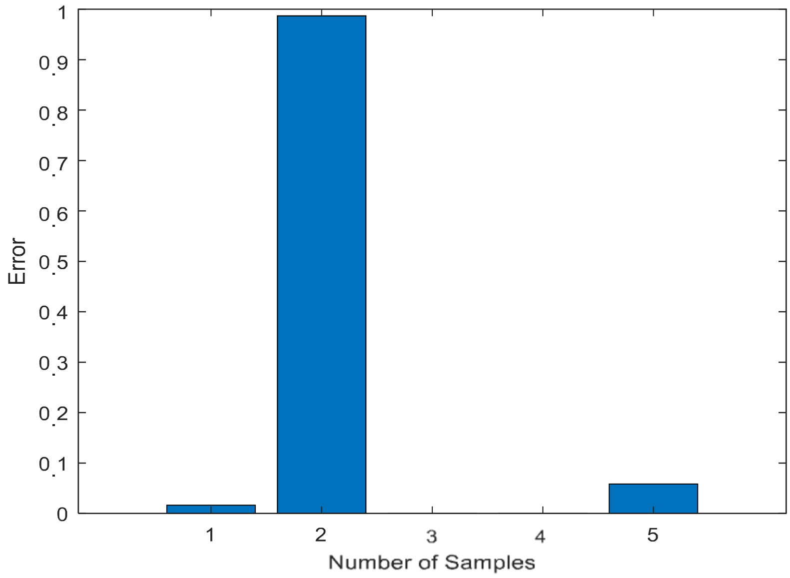


Figure 6.10 Error graph of availability data sets (2-8-1) of study area-2

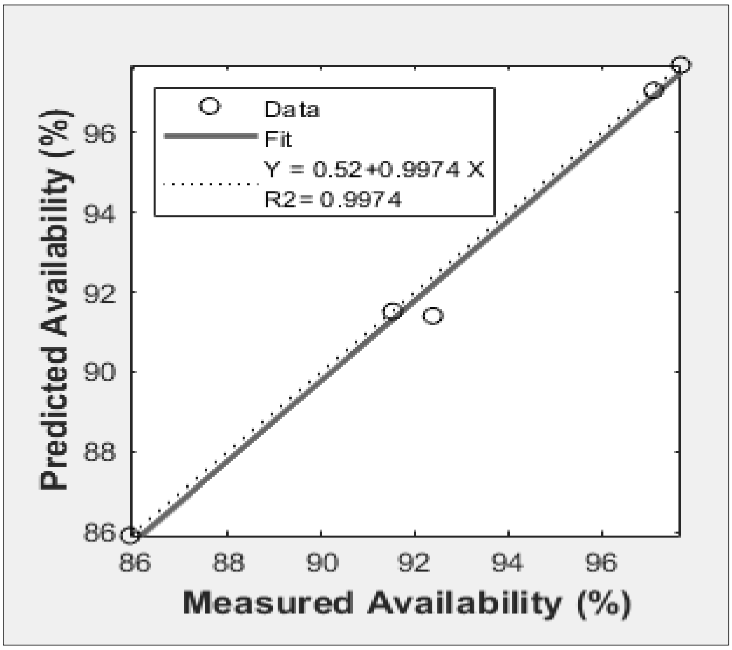


Figure 6.11 Predicted and computed ANN availability results of the Training data sets of study area-2

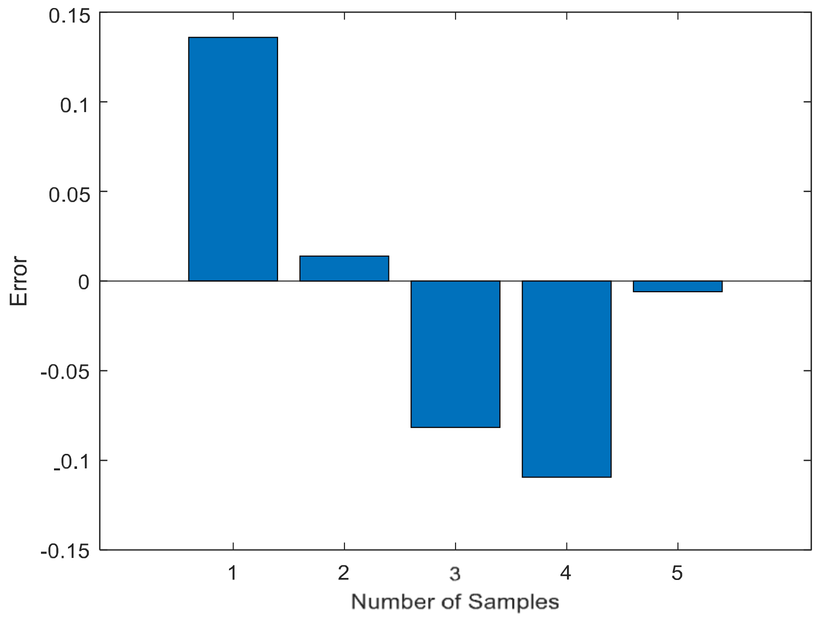


Figure 6.12 Error graph of availability data sets (2-4-1) of study area-3

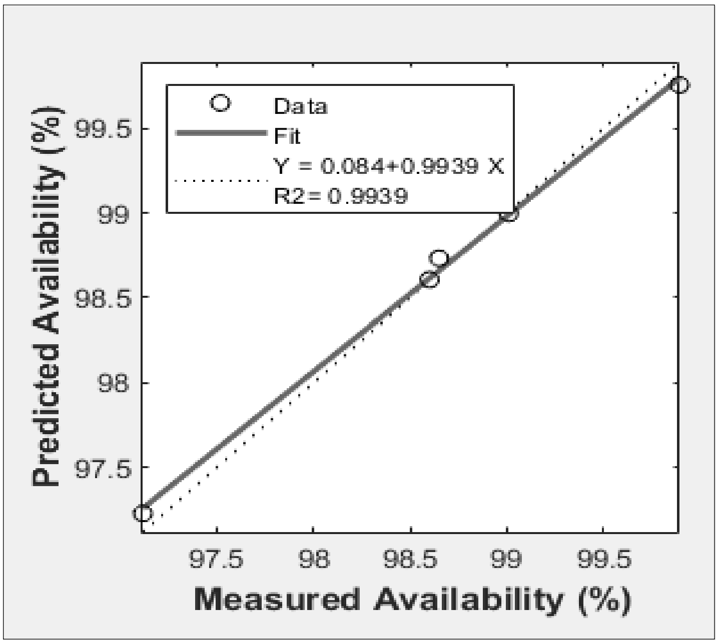


Figure 6.13 Predicted and computed ANN availability results of the Training data sets of study area-3

6.1.3 Development of ANN Simulation Model for Reliability

ANN model of reliability was developed by utilizing MTBF and MTTR metrics. TRAINLM learning function has been used for the training process. After selecting the training function, the adaption learning function was selected as LEARNGDM (Gradient Descent with momentum weight and bias learning function). TANSIG transfer function was selected for the hidden layer and linear function (PURELIN) for the output layer. The model was tested by varying the number of neurons from 4 to 15 and trained up to 1000 iterations for obtaining the best optimum results. The selection of the optimum value of R^2 was done based on root Mean Square Error (RMSE) (Equation 6.1) value. From the obtained results it was noticed that R^2 (0.99815) was optimum at 0.034731 (RMSE) for neuron number-8 (Table 10). The Training performance of the reliability of various neurons is given in Table 6.11. The developed optimal ANN reliability model of LM-8 for study area-1 is shown in Figure 6.14. Similarly, for study area-2, the model was tested by varying the number of neurons from 4 to 12 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9961) was optimum at 0.3014 (RMSE) for LM-10 (Table 12). The Training performance of the reliability of various neurons is given in Table 6.13. The developed optimal ANN reliability model of LM-10 for study area-2 is shown in Figure 6.15. Similarly, for study area-3, the model was tested by varying the number of neurons from 4 to 15 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9946) was optimum at 0.3012 (RMSE) for LM-10 (Table 6.14). The Training performance of the reliability of various neurons is given in Table 6.15. The developed optimal ANN reliability model of LM-10 for study area-3 is shown in Figure 6.16. The predicted values of the optimum R^2 of study area-1, 2 and 3 are then recorded for validation.

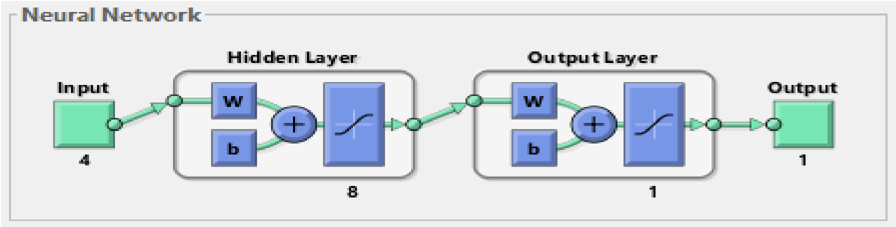


Figure 6.14 Developed ANN reliability model of neuron-8 for study area-1

Table 6.10 Training performance of reliability for various neurons of study area-1

Sl.No.	Number of Neurons	R^2	RMSE
1	4	0.99287	0.64565
2	5	0.98050	0.55281
3	6	0.99569	0.49692
4	7	0.99283	0.63317
5	**8**	**0.99815**	**0.34731**
6	9	0.90955	0.94432
7	10	0.98106	0.88473
8	11	0.97838	0.91630
9	12	0.98125	0.10525
10	13	0.97320	0.91226
11	14	0.98116	0.55121

Table 6.11 Predicted values of reliability from ANN model for study area-1

Sl. No	Machine	MTBF (hours)	η	β	γ	Reliability (%)
1	LH21	5.34	537	0.805	296.9	69.10
2	LH22	3.65	365.4	1.218	272.4	66.47
3	LH24	3.05	348.5	0.925	319.5	58.63
4	LH25	3.00	619.4	1.095	283.1	60.03
5	LH26	3.21	286.4	1.387	438.3	59.97
6	LH27	3.83	1072	2.492	0	69.44
7	LH28	3.58	411.2	1.293	307.1	65.27
8	LH29	3.91	869.6	3.263	0	69.43
9	LH30	3.90	2326	7.048	-769	69.40
10	LH31	3.72	672.2	1.105	479.2	67.23

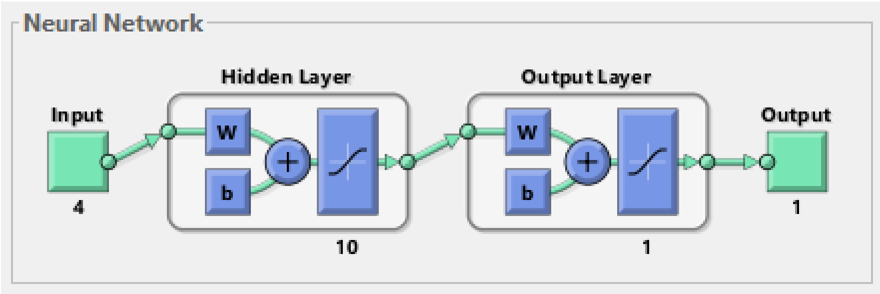


Figure 6.15 Developed ANN reliability model of neuron-10 for study area-2

Table 6.12 Training performance of reliability for various neurons for study area-2

Sl. No	Number of Neurons	R^2	RMSE
1	4	**0.9481**	**0.7828**
2	5	0.9866	0.5161
3	6	0.8815	0.9177
4	7	0.9741	0.6100
5	8	0.9091	0.4127
6	9	0.9869	0.5001
7	**10**	**0.9961**	**0.3014**
8	11	0.9771	0.9168
9	12	0.9864	0.5421

Table 6.13 Predicted values of reliability from ANN model for study area-2

Sl. No	Machine	MTBF (hours)	η	B	γ	Reliability (%)
1	LHD1	101.47	29.88	0.8365	68.3	64.59
2	LHD2	112.7	191.8	1.625	0	72.71
3	LHD3	459.45	446.5	0.7041	487.4	87.49
4	LHD4	190.56	159.5	2.048	0	84.48
5	LHD5	485.81	245.9	1.912	0	85.28

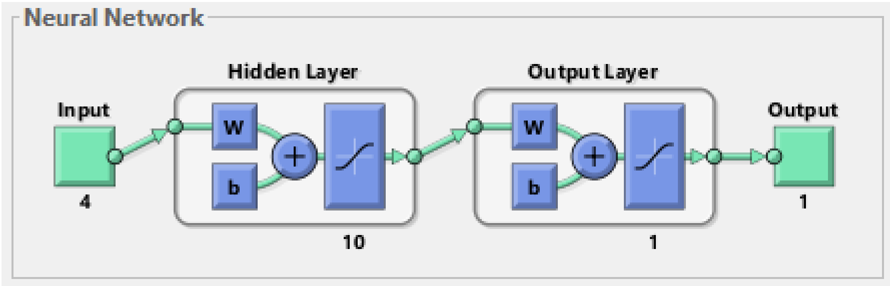


Figure 6.16 Developed ANN reliability model of neuron-10 for study area-3

Table 6.14 Training performance of reliability for various neurons for study area-3

Sl. No	Number of Neurons	R^2	RMSE
1	4	0.8532	0.8201
2	5	0.7475	0.8701
3	6	0.7845	0.9881
4	7	0.8887	0.9010
5	8	0.8583	0.8991
6	9	0.8434	0.9012
7	**10**	**0.9946**	**0.3012**
8	11	0.9045	0.6621
9	12	0.8490	0.9124

Table 6.15 Predicted values of reliability from ANN model for study area-3

Sl. No	Machine	MTBF (hours)	η	β	Γ	Reliability (%)
1	E1-LHD1	72.68	162.9	1.541	0	72.38
2	E2-LHD2	64.35	208.3	1.802	-4.245	68.89
3	E3-LHD3	85.48	233.3	3.264	-93.92	68.87
4	E5-LHD5	84.58	70.48	0.668	24.75	84.93
5	E6-LHD6	87.38	570.9	10.16	-437.4	68.87

6.1.4 Validation of the Computed Reliability Results with ANN Predicted Results

Similarly, the developed model of ANN for reliability was optimized at neuron number-8 (4-8-1) for study area-1 and study area-2, and 3 at neuron number-10 (4-10-1). Predicted values of reliability for study area-1 (Table 6.11), 2 (Table 6.13) and 3 (Table 6.15) were recorded corresponding to the optimized neurons of developed models for validation purpose. The computed reliability results were validated with the predicted values for study area-1 (Table 6.16), 2 (Table 6.17) and 3 (Table 6.18).

Table 6.16 Validation of predicted reliability ANN results of study area-1

Sl.No.	Machine	Computed Reliability (%)	Predicted ANN Reliability (%)	Percentage Error (%)
1	LH21	69.11	69.10	0.00
2	LH22	66.48	66.47	0.00
3	LH24	56.77	58.63	-1.86
4	LH25	60.03	60.03	-0.00
5	LH26	59.98	59.97	6.02e-05
6	LH27	68.98	69.44	-0.78
7	LH28	65.63	65.27	0.35
8	LH29	69.44	69.43	0.00
9	LH30	69.41	69.40	0.00
10	LH31	67.24	67.23	0.00

Table 6.17 Validation of predicted reliability ANN results of study area-2

Sl.No.	Machine	Computed Reliability (%)	Predicted ANN Reliability (%)	Percentage Error (%)
1	LHD1	64.77	64.59	-1.57e-08
2	LHD2	72.71	72.71	0.82
3	LHD3	87.49	87.49	2.95e-06
4	LHD4	84.48	84.48	-0.17
5	LHD5	85.29	85.28	3.36e-11

Table 6.18 Validation of predicted reliability ANN results of study area-3

Sl.No.	Machine	Computed Reliability (%)	Predicted ANN Reliability (%)	Percentage Error (%)
1	E1-LHD1	84.77	72.38	12.38
2	E2-LHD2	69.82	68.89	0.92
3	E3-LHD3	88.08	68.87	19.22
4	E5-LHD5	68.87	84.93	-16.06
5	E6-LHD6	87.80	68.87	18.93

In order to obtain a better understanding of the experimental and predicted ANN reliability values, the error for the training and testing data sets has been drawn and is shown in Figures 6.17 (study area-1), 6.19 (study area-2) and 6.21 (study area-3). From the Figure 6.17 of study area-1, minimum error value (-1.86%) was noticed for LH24 and the maximum error value (0.35%) was noticed for LH28. Similarly, from Figure 6.19 of study area-2, minimum error value (-0.17%) was noticed for LHD4 and the maximum error value (0.82%) was noticed for LHD2. Figure 6.21 of study area-3, minimum error value (-16.06%) was noticed for E4-LHD4 and the maximum error value (19.22%) was noticed for E3-LHD3. Hence, the maximum error is within the limit (less than 20%).

The comparison of predicted results with computed reliability values for study area-1, 2 and 3 are shown in Figure 6.18, Figure 6.20 and Figure 6.22 respectively. These figures shows that the predicted results were found to be closer to the computed values. Hence, it was concluded that the neural network is an appropriate model for the developed network models.

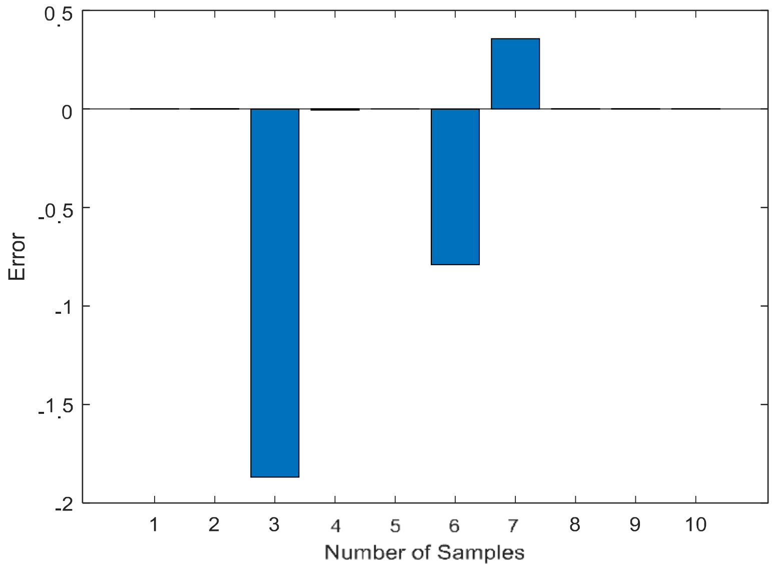


Figure 6.17 Error graph of reliability data sets (4-8-1) of study area-1

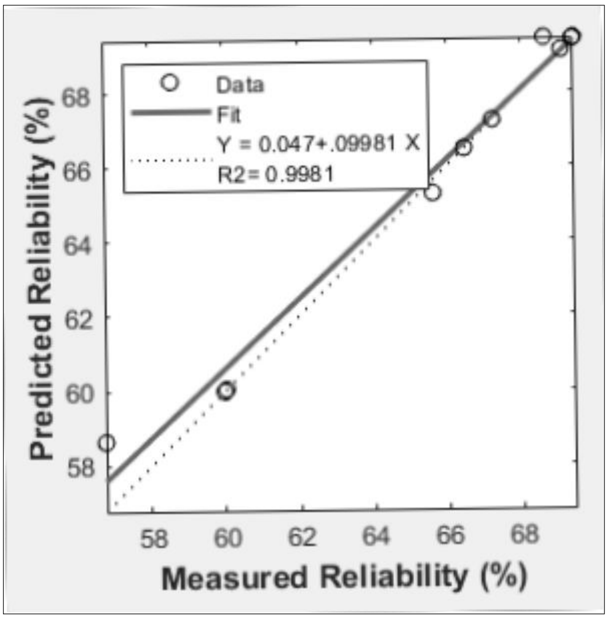


Figure 6.18 Predicted and computed ANN reliability results of the Training data sets of study area-1

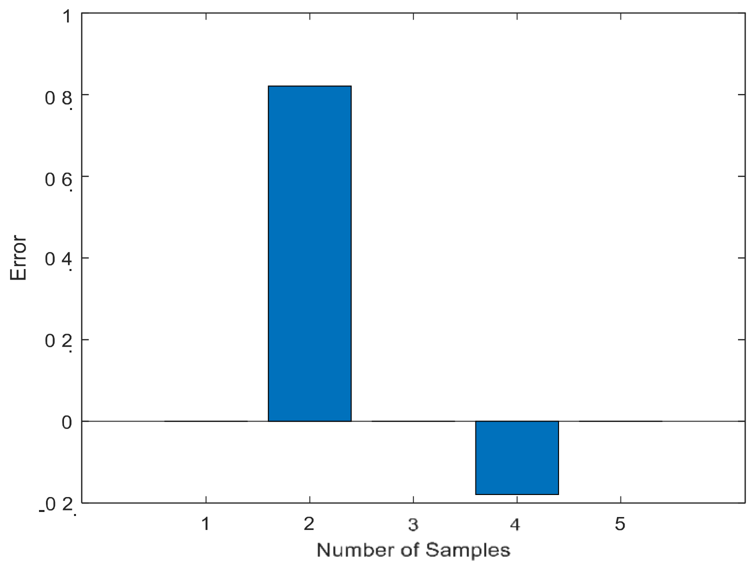


Figure 6.19 Error graph of reliability data sets (4-10-1) of study area-2

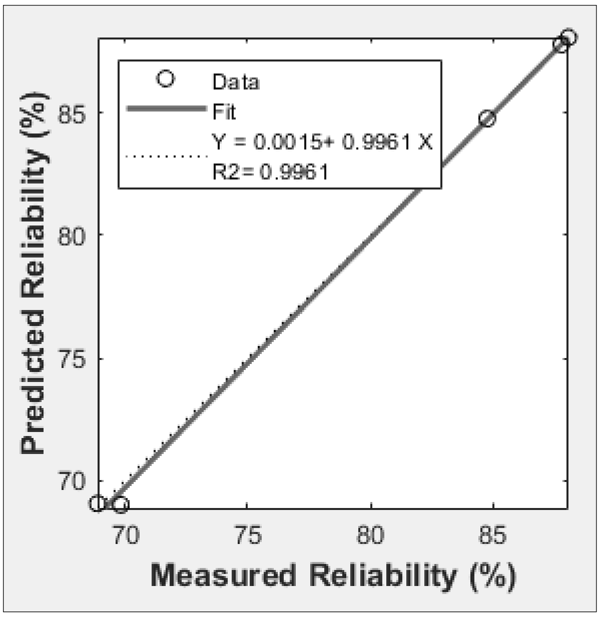


Figure 6.20 Predicted and computed ANN reliability results of the Training data sets of study area-2

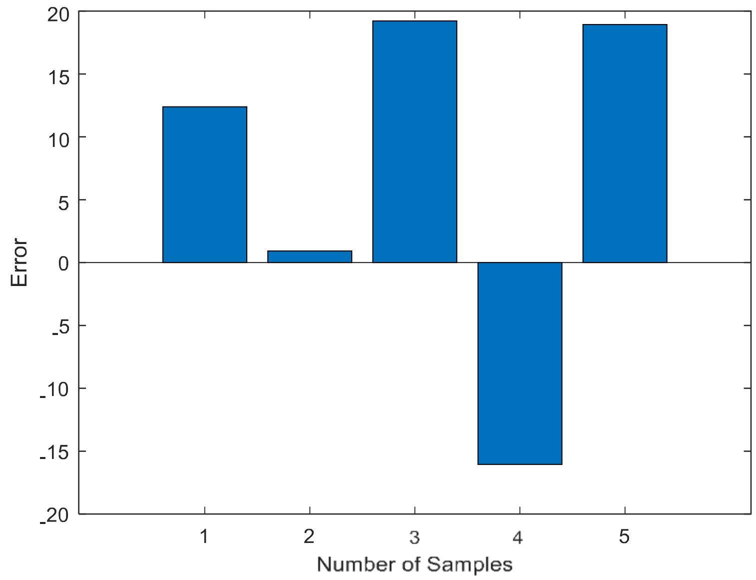


Figure 6.21 Error graph of reliability data sets (4-10-1) of study area-3

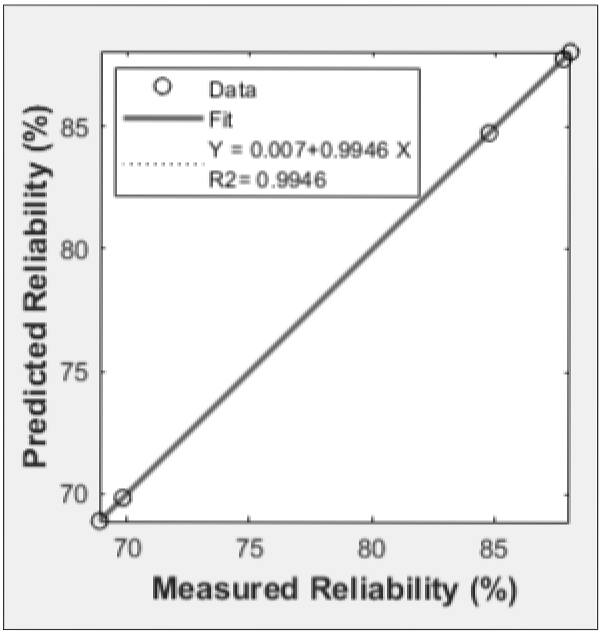


Figure 6.22 Predicted and computed ANN reliability results of the training data sets of study area-3

6.1.5 Development of ANN Simulation Model for Preventive Maintenance (PM)

ANN model of PM was developed by utilizing the MTBF and MTTR metrics. TRAINLM learning function has been used for training purposes. After selecting the training function, the adaption learning function was selected as LEARNGDM (Gradient Descent with momentum weight and bias learning function). TANSIG transfer function was selected for the hidden layer and linear function (PURELIN) for the output layer. The model was tested by varying the number of neurons from 4 to 16 and trained up to 1000 iterations for obtaining the best optimum results. The selection of optimum value of R^2 was done based on Root Mean Square Error (RMSE) (Equation 6.1) value. From the obtained results it was noticed that R^2 (0.9990) was optimum at 0.001659 (RMSE) for LM-15 (Table 6.19). The Training performance of the PM of various neurons is given in Table 6.20. The developed optimal ANN PM model of LM-15 for study area-1 is shown in Figure 6.23. Similarly, in the study area-2, the model was tested by varying the number of neurons from 4 to 10 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9941) was optimum at 0.0014 (RMSE) for LM-6 (Table 6.21). The Training performance of the PM of various neurons is given in Table 6.22. The developed optimal ANN PM model of LM-6 for study area-2 is shown in Figure 6.24. Similarly, for study area-3, the model was tested by varying the number of neurons from 4 to 10 and trained up to 1000 iterations for obtaining the best optimum results. From the obtained results it was noticed that R^2 (0.9998) was optimum at 0.0016 (RMSE) for LM-4 (Table 6.23). The Training performance of PM of various neurons is given in Table 6.24. The developed optimal ANN PM model of LM-4 for study area-3 is shown in Figure 6.25. The predicted values of the optimum R^2 of study area-1, 2 and 3 are then recorded for validation purposes.

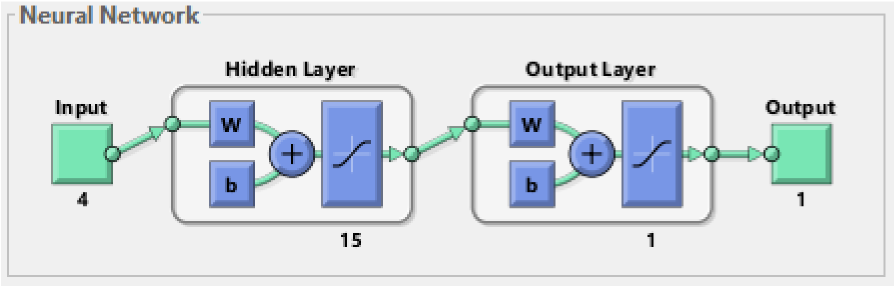


Figure 6.23 Developed ANN PM model of neuron-15 for study area-1

Table 6.19 Training performance of the PM for various neurons of study area-1

Sl. No	Number of Neurons	R^2	RMSE
1	4	0.9761	0.008157
2	5	0.9982	0.002175
3	6	0.9555	0.013742
4	7	0.9869	0.005191
5	8	0.9839	0.007723
6	9	0.9008	0.014164
7	10	0.9989	0.001820
8	11	0.9540	0.006734
9	12	0.9884	0.004716
10	13	0.9772	0.007155
11	14	0.9053	0.014652
12	**15**	**0.9990**	**0.001659**
13	16	0.9864	0.004618

Table 6.20 Predicted values of PM from ANN model for study area-1

Sl. No	Machine	Expected Reliability (%)	η	β	γ	PM (hours)
1	LH21	90.00	537	0.8054	296.9	540.96
2	LH22	90.00	365.4	1.218	272.4	370.21
3	LH24	90.00	348.5	0.925	319.5	349.01
4	LH25	90.00	619.4	1.095	283.1	656.69
5	LH26	90.00	286.4	1.387	438.3	324.72
6	LH27	90.00	1072	2.492	0	1071.95
7	LH28	90.00	411.2	1.293	307.1	411.55
8	LH29	90.00	869.6	3.263	0	869.79
9	LH30	90.00	2326	7.048	-769	1250.99
10	LH31	90.00	672.2	1.105	479.2	674.01

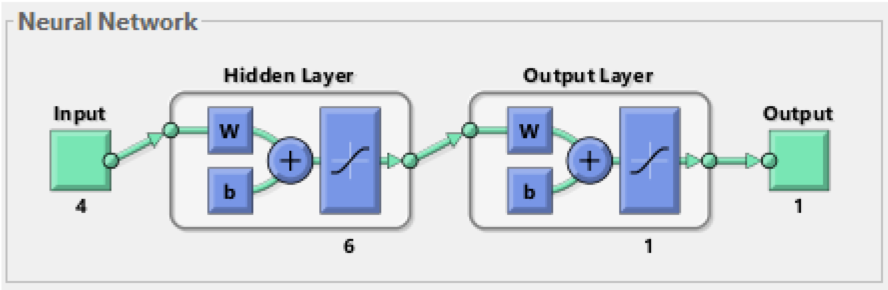


Figure 6.24 Developed ANN PM model of neuron-6 for study area-2

Table 6.21 Training performance of PM for various neurons of study area-2

Sl. No	Number of Neurons	R^2	RMSE
1	4	0.9839	0.0048
2	5	0.6023	0.0891
3	**6**	**0.9941**	**0.0014**
4	7	0.9811	0.0044
5	8	0.9767	0.0713
6	9	0.9721	0.0691
7	10	0.8713	0.0161

Table 6.22 Predicted values of PM from ANN model for study area-2

Sl. No	Machine	Expected Reliability (%)	η	β	Γ	PM (hours)
1	LHD1	90.00	29.88	0.8365	68.3	70.51
2	LHD2	90.00	191.8	1.625	0	45.93
3	LHD3	90.00	446.5	0.7041	487.4	505.73
4	LHD4	90.00	159.5	2.048	0	53.58
5	LHD5	90.00	245.9	1.912	0	74.85

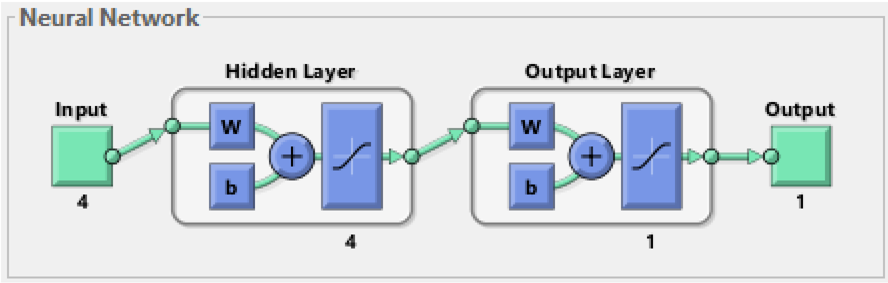


Figure 6.25 Developed ANN PM model of neuron-4 for study area-3

Table 6.23 Training performance of the PM for various neurons of study area-3

Sl. No	Number of Neurons	R^2	RMSE
1	**4**	**0.9998**	**0.0016**
2	5	0.9816	0.0041
3	6	0.7814	0.0068
4	7	0.8881	0.0038
5	8	0.9010	0.0044
6	9	0.9889	0.0050
7	10	0.8971	0.0037

Table 6.24 Predicted values of PM from ANN model for study area-3

Sl. No.	Machine	Expected Reliability (%)	η	β	γ	PM (hours)
1	E1-LHD1	90.00	162.9	1.541	0	35.48
2	E2-LHD2	90.00	208.3	1.802	-4.245	56.29
3	E3-LHD3	90.00	233.3	3.264	-93.92	23.11
4	E5-LHD5	90.00	70.48	0.668	24.75	24.26
5	E6-LHD6	90.00	570.9	10.16	-437.4	20.37

6.1.6 Validation of the Computed Preventive Maintenance (PM) Results with ANN Predicted Results

Likewise, the developed model of ANN for PM was optimized at neuron number-15 (4-15-1) for study area-1 and 6 for study area-2 (4-6-1), and 4 for (4-4-1) study area-23. Predicted values of PM for study area-1 (Table 6.20), 2 (Table 6.22) and 3 (Table 6.24) were recorded corresponding to the optimized neurons of developed models for validation purpose. The computed PM results were validated with the predicted values for study area-1 (Table 6.25), 2 (Table 6.26) and 3 (Table 6.27).

Table 6.25 Validation of predicted PM-ANN results of study area-1

Sl.No.	Machine	Computed PM (hours)	Predicted ANN PM (hours)	Percentage Error (hours)
1	LH21	538	540.96	-0.00
2	LH22	367	370.21	-0.01
3	LH24	349	349.01	1.44
4	LH25	620	656.69	-32.43
5	LH26	288	324.72	-0.13
6	LH27	1072	1071.95	0.01
7	LH28	412	411.55	82.48
8	LH29	870	869.79	0.01
9	LH30	1257	1250.99	2.43
10	LH31	673	674.01	-0.02

Table 6.26 Validation of predicted PM-ANN results of study area-2

Sl.No.	Machine	Computed PM (hours)	Predicted ANN PM (hours)	Percentage Error (hours)
1	LHD1	70	70.51	21.49
2	LHD2	48	45.93	-0.03
3	LHD3	506	505.73	0.53
4	LHD4	53	53.58	-64.22
5	LHD5	76	74.85	-0.03

Table 6.27 Validation of predicted PM-ANN results of study area-3

Sl.No.	Machine	Computed PM (hours)	Predicted ANN PM (hours)	Percentage Error (hours)
1	E1-LHD1	38	35.48	6.27
2	E2-LHD2	56	56.29	2.34e-05
3	E3-LHD3	23	23.11	2.49
4	E5-LHD5	27	24.26	2.91e-07
5	E6-LHD6	20	20.37	-9.42

In order to obtain a better understanding of the experimental and predicted ANN reliability values, the error for the training and testing data sets has been drawn and is shown in Figures 6.26 (study area-1), 6.28 (study area-2) and 6.30 (study area-3). From the Figure 6.26 of study area-1, minimum error value (-32.43 hours) was noticed for LH25 and the maximum error value (82.48 hours) was noticed for LH28. Similarly, from Figure 6.28 of study area-2, minimum error value (-64.22 hours) was noticed for LHD4 and the maximum error value (21.49 hours) was noticed for LHD1. Figure 6.30 of study area-3, minimum error value (-9.42 hours) was noticed for E6-LHD6 and the maximum error value (6.27 hours) was noticed for E1-LHD1. Hence, the maximum error is within the limit (less than 100 hours).

The comparison of predicted results with computed PM values for study area-1, 2 and 3 are shown in Figure 6.27, Figure 6.29 and Figure 6.31 respectively. These figures shows that the predicted results were found to be closer to the computed values. Hence, it was concluded that the neural network is an appropriate model for the developed network models.

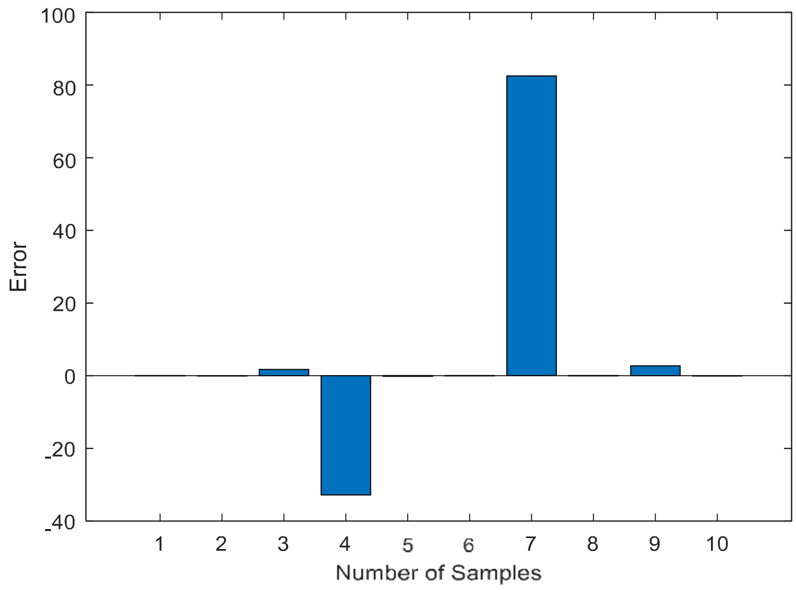


Figure 6.26 Error graph of PM data sets (4-15-1) of study area-1

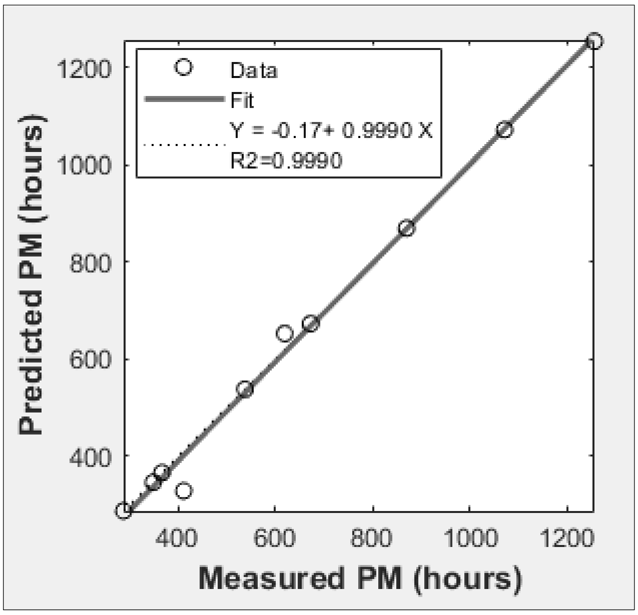


Figure 6. 27 Predicted and computed ANN PM results of the Training data sets of study area-1

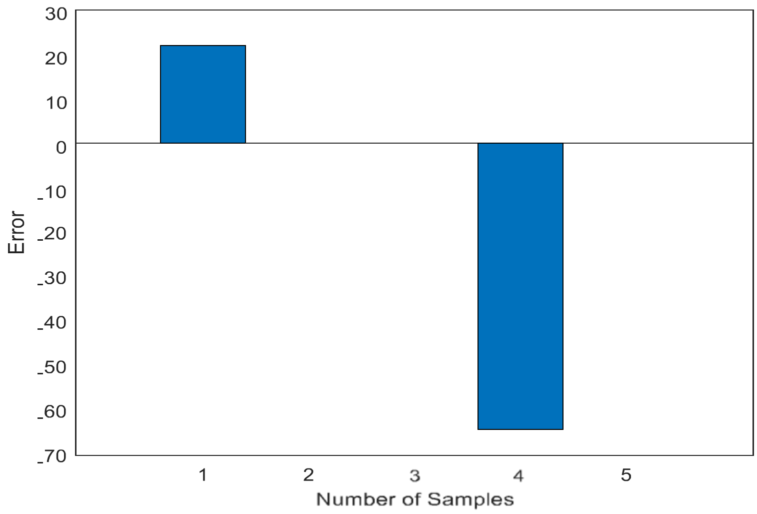


Figure 6.28 Error graph of PM data sets (4-6-1) of study area-2

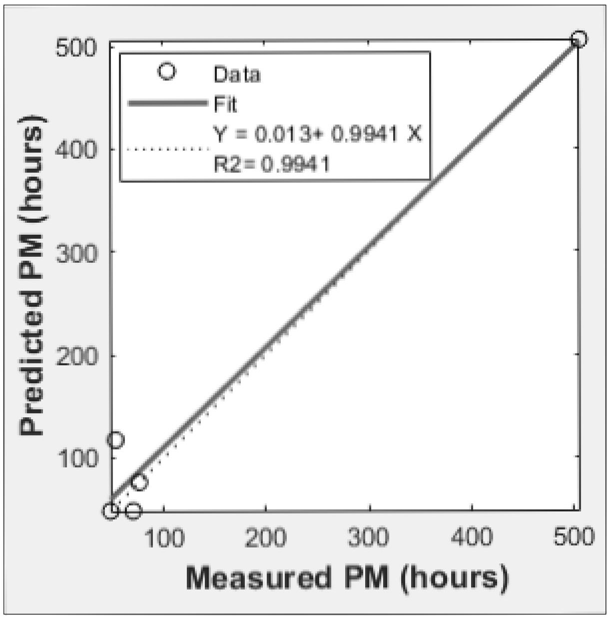


Figure 6.29 Predicted and computed ANN PM results of the training data sets of study area-2

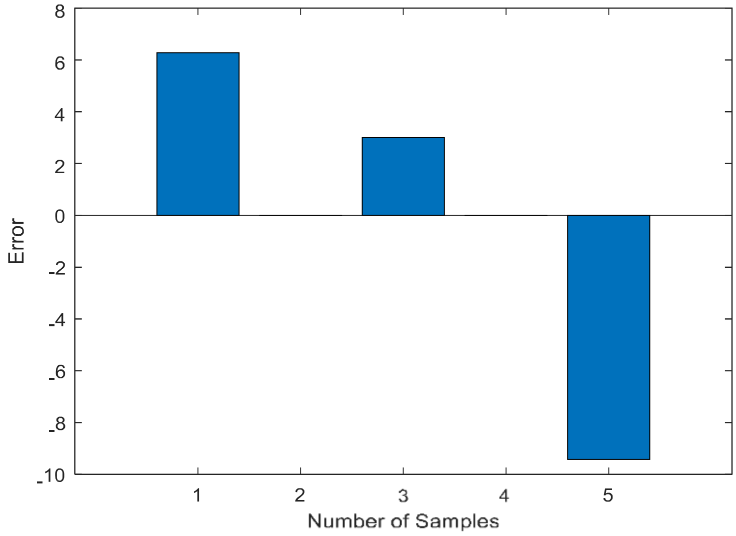


Figure 6.30 Error graph of PM data sets (4-4-1) of study area-3

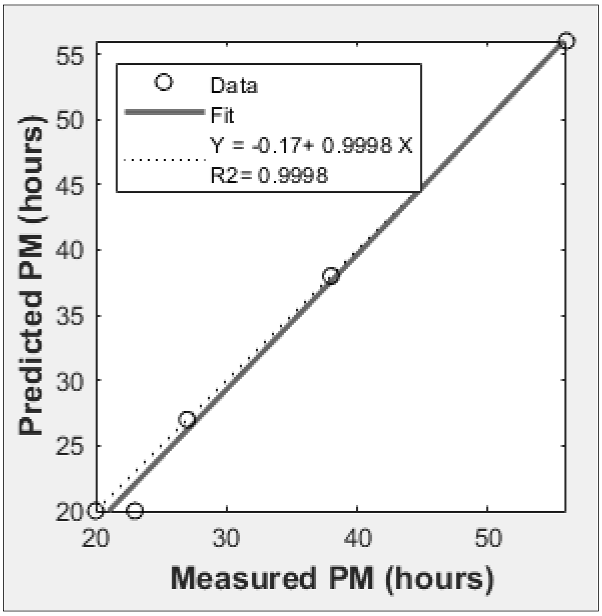


Figure 6.31 Predicted and computed ANN PM results of the training data sets of study area-3

6.2 FUZZY FAILURE MODE EFFECT ANALYSIS (FUZZY-FMEA)

6.2.1 Drawbacks of Conventional FMEA

The goal of Failure Mode Effect Analysis (FMEA) is to discover and prioritize the possible breakdown types through calculation of Risk Priority Number (RPN) values. FMEA based RPN evaluations are popular for evaluating all kinds of product and process investigations (Rajiv Kumar Sharma. et. al., 2005). This technique is popular due to its accuracy and ease of use. However, unfortunately, numerous drawbacks are associated with its sensible implementation in actual working situations in production or process industries.

The critical disadvantages include:

- In RPN analysis, the same kind of identical values can be obtained for different data set points of Severity (S), Occurrence (O) and Detection (D); however, the risk assessment might be completely different (Sachdeva. A. et al. 2009).
- The qualified significance between the S, O and D parameter rating~~s~~.
- The dissimilarity of hazard illustrations among the breakdown modes having identical RPN (Rajiv, Kumar. Sharma. et. al., 2005).

For example, let us say that the risk indexed factors for the machinery components X and Y are S=6, O=2, D=5 and S=3, O=4, D=5. Since RPN is the product of S, O and D, both components have a similar RPN value i.e., RPN=60. However, the degree of a risk factor for these components may not be the same. The other difficulty of RPN grading is that it ignores the qualified significance between S, O and D. As a result, these three parameters are assumed to have identical consequences, but in actual realistic appliances, qualified significance between the factors should exist. Similarly, for example, state component 1, with risk indexed parameters of S=5, O=4, and D=5 might have the lowest value of RPN i.e. 100. Whereas, the other alternative component 2, with moderately high risk, indexed parameters of S=6, O=8, D=4, has RPN= 192. There is a huge difference between RPN values of these components; however, it is necessary to prioritize the components with respect to RPN values.

Important efforts have been made within FMEA to overcome the inadequacy of conventional RPN. Particularly fuzzy modelling with a fuzzy If-then rule base has been recommended to overcome the disadvantages. In the investigation of the Fuzzy based FMEA model, a specialist can describe the risk indexed factors such as S, O and D using a fuzzy linguistic path (Chen. S.H. 1985 and Bowles. J. B and Pelaez. C. E. 1995).

6.2.2 Significance of the Fuzzy Logic Technique

Fuzzy logic is an appropriate technique that is used to estimate the output response from given input data. There are a wide variety of reasons why the business commentators use a fuzzy logic system (Kusumadewi. S. 2002):

- The Fuzzy logic concept is very easy to understand. The fundamentals of mathematics are also uncomplicated in the Fuzzy Interface System.
- This is flexible and can tolerate the data if any inappropriate result exists in the datasets.
- This technique can model complex non-linear functions in a short period.
- This approach can also build up the experience of specialists without the need for additional training.
- This technique will work based on simple natural language.

6.2.3 Fuzzy FMEA Methodology

According to Wang, L. X (2008), the fuzzy methodology is a significant theory in risk evaluation process which deals with the breakdown data of the system. In Fuzzy-FMEA the risk indexed parameters such as Severity (S), Occurrence (O) and Detection (D) are fuzzified with suitable membership functions. This is a knowledge-based approach and can be created with proficiency and knowledge in the form of Fuzzy IF-THEN rules (Tay, K. M and Lim, C. P. 2006). More sensible and suitable knowledge-based models can be built using expert knowledge and decisions. The fuzzy conclusion is then de-fuzzified to acquire the RPN value. The flowchart of Fuzzy-FMEA technique, i.e. Fuzzification, Fuzzyule base and De-fuzzification is shown in Figure 6.32.

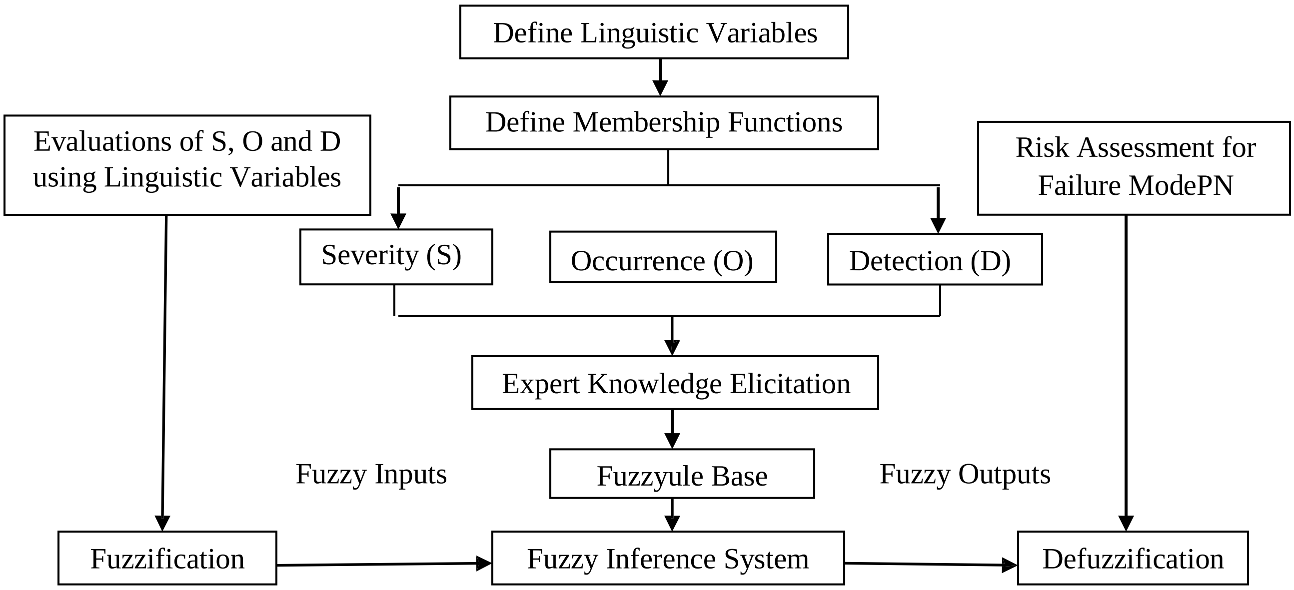


Figure 6.32 Flow chart of Fuzzy-FMEA Technique

- **Fuzzification**

Fuzzification is a process used to transform input parameters into membership degree quantities, which express the input parameters in the form of qualitative linguistic terms (Rajiv Kumar Sharma. et al. 2005). Specialist decisions and knowledge can be utilized to describe the degree of membership function for a particular variable. Along with Fuzzification, a fuzzy logic controller acquires input information, known as the fuzzy variable, and examines it as outlined by client characterized diagrams called membership functions.

- **Fuzzy rule base**

The fuzzy rule base explains the level of criticality of a system for each combination of input variables. In general, the combination of input variables can be created in linguistic form, for example, by using rule-based logic like “if-then”, “or-else” etc. This can be created in two different ways namely; (i) Familiarity and proficiency of a specialist (ii) Process of the Fuzzy based model (Yang, Guanbin. 2007). Experts’ judgment and experience can be used to define the degree of membership function for a variable.

- **De-fuzzification**

De-fuzzification is a process of looking at standard results after they have been normally included and that they will be the final output responses of the fuzzy controller. During defuzzification, the controller exchanges the fluffy yield into response information (Rajiv Kumar Sharma et, al. 2005).

6.2.4 Fuzzy-FMEA for LHD Performance Investigation

Fuzzy set theory is a way to deal with exchanging the vulnerability of hypothetical relations into numerical systems by a pattern has been developing in FMEA writing which utilizes fuzzy linguistic terms for depicting the three hazard factors of S, O, and D. Many of the researchers assumed that Fuzzy FMEA approach is a great foundation for obtaining accurate responses (Keskin, G. A and Özkan, C. 2009), and (Gargama, H and Chaturvedi, S. K 2011). The vast majority of the current investigations into fuzzy FMEA are by utilizing 'If-Then rules. The present research work portrays the exact and sensible positioning of the needs of different disappointment modes by the usage of regular FMEA and proposed Fuzzy FMEA approaches. In this study, LHD machines deployed in three different mines were considered for risk analysis. Breakdown data for 24 months of study area-1, 2, and 3 were taken into consideration for the analysis. An If-Then rule base has been created using a fuzzy inference system (FIS), which after de-fuzzification generates the fuzzy risk priority number (FRPN). The Fuzzy Linguistic evaluation model was developed using the MATLAB 7.0 toolbox platform.

The proposed Fuzzy-FMEA approach provides information on the possibility of the occurrence of the various potential failure modes with identical RPN values. This helps to reduce the burden of the prioritization of RPN rankings. In general, it was assumed that all the risk indexed parameters are equally important. The value of RPN with ‘n’ number of failure modes is estimated from the following expression (Equation 6.2) (Zimmermann, H. 1996) and (Zafiropoulos, E.P and Dialynas, E. N. 2005):

$$\mathrm{RPN} = \prod_{i,j=1}^{n} X_{ij} \qquad (6.2)$$

Where $1 \leq i \leq n$; $1 \leq j \leq n$;

Let ‘Xij’ indicate the position of S, O, and D of failure mode ‘Fi’, where i = 1, 2, 3… n and j = 1, 2, 3…n.

Xij accurately receives the positions of 1 to 10 sequentially. The quantitative scale of ranking for S, O and D are given in Table 5.10, 5.11, and 5.12 in Chapter-5.

The prioritization of risk indexed parameters are evaluated with a three-stage process;

- Critical Failure Mode Index (CFMI)

  CFMIi, j= min [max (S11. S12, S13…S1n-1,S1n), max (O11, O12, O13…O1n-1, O1n) and max (D11, D12, D13…D1n-1, D1n)]
- Risk Priority Code (RPC)

  RPCi,j= Ni,j

  Where Ni,j indicates the number of samples or failures in the consequent to “i,j” for which Xi,j≥ CFMIi,j
- Critical Breakdown Mode (CBM)

  CBMi= the breakdowns are consequent to max. Ni,j.

The ranking of S, O, and D are assigned based on expert decisions in a range using a scale of 1 to 10 scale. RPN values were calculated for each potential failure mode with the multiplication of risk indexed parameters (S, O, and D). The general structure of risk indexed parameters and RPN metrics are given in Table 6.28. The estimated metrics of RPN corresponding to the risk indexed parameter rankings of study area-1, 2, 3 using conventional FMEA approach are given in Table 5.16, 5.17, and 5.18 in Chapter-5.

Table 6.28 General structure of risk indexed parameters and RPN metrics

Sub System	Failure Type	Severity (S)	Occurrence (O)	Detection (D)	RPN
SSE	F1	X11	X12	X13	RPN1
SSBr	F2	X21	X22	X23	RPN2
SSTy	F3	X31	X32	X33	RPN3
.	.	.	.	.	.
.	.	.	.	.	.
SSH	F9	X91	X92	X93	RPN9
SSM	F10	X101	X102	X103	RPN10

In this analysis, three factors were considered as input factors for the fuzzy system. These were evaluated using well defined If-Then rules prepared in the MATLAB Fuzzy logic toolbox. The membership function was derived, initially, to produce the fuzzy rule base. The MATLAB rule Viewer was kept open throughout the reproduction procedure and can be utilized to get to the Membership Function Editor and rule Editor. The function rule Editor is used to edit the list of rules, which characterizes the conduct of the framework. Input variables/membership functions can be added using the Fuzzy Interface System (FIS) Editor.

The outputs of the RPN fuzzy values are categorized into nine interval classes: Hazardous/ Very High–V.H, High-H, Moderate-M, Moderately Low-ML, Moderately High-MH, Low-L, Very Low-V.L, Remote-R, Remotely High-RH and Remotely Low-RL. The membership function of the output variable and its parameters can be determined based on the type of curve used (Figure 6.33 (a), (b), and (c) for study area-1, 2, and 3).

The resulting fuzzy input is evaluated using the fuzzy rules (IF-THEN rule). The input variables used are S, O and D, with five levels (Hazardous/ Very High (V.H), High (H), Moderate (M), Low (L) and None (N)) to obtain the fuzzy rule base combinations. The combination of this FMEA fuzzy rule base system for study area-1 is given in the example below:-

Combination of the rule base in fuzzy FMEA (Rengith V and Dilip Madhavan. 2018)*:*

- IF Severity is L, Occurrence is M and Detection is L then FRPN is L
- IF Severity is H, Occurrence is H and Detection is H then FRPN is H Critical
- IF Severity is H and Occurrence is H and Detection is V.H then FRPN is M
- IF Severity is L and Occurrence is V.H and Detection is V.H then FRPN is L
- IF Severity is M. Occurrence is M and Detection is M then FRPN is H Critical
- IF Severity is L, Occurrence is M and Detection is M then FRPN is V.H Critical
- IF Severity is L and Occurrence is M and Detection is M then FRPN is H
- IF Severity is H, Occurrence is V.H and Detection is V.H then FRPN is M
- IF Severity is M, Occurrence is L and Detection is L then FRPN is V.H Critical
- IF Severity is V.H and Occurrence is L and Detection is H then FRPN is H

- IF Severity is H and Occurrence is M and Detection is H then FRPN is M
- IF Severity is L and Occurrence is H and Detection is H then FRPN is M
- IF Severity is M, Occurrence is L and Detection is V.H then FRPN is N
- IF Severity is V.H, Occurrence is L and Detection is V.H then FRPN is L
- IF Severity is V.H, Occurrence is L and Detection is H then FRPN is M
- IF Severity is H, Occurrence is L and Detection is V.H then FRPN is L

The formulation of the fuzzy rule (IF-THEN rule) is done by considering the severity value is to be most critical input for the fuzzy RPN value. So that, if the Severity (S) value is Very High (VH) then the corresponding fuzzy RPN value is also Very High (VH), in spite of the value obtained for Occurrence (O) and Detection (O). The resulting fuzzy RPN value indicates the priority level of risk to be addressed. High fuzzy RPN values indicate that the risk should have greater priority. The calculation of the RPN fuzzy value is performed using MATLAB.

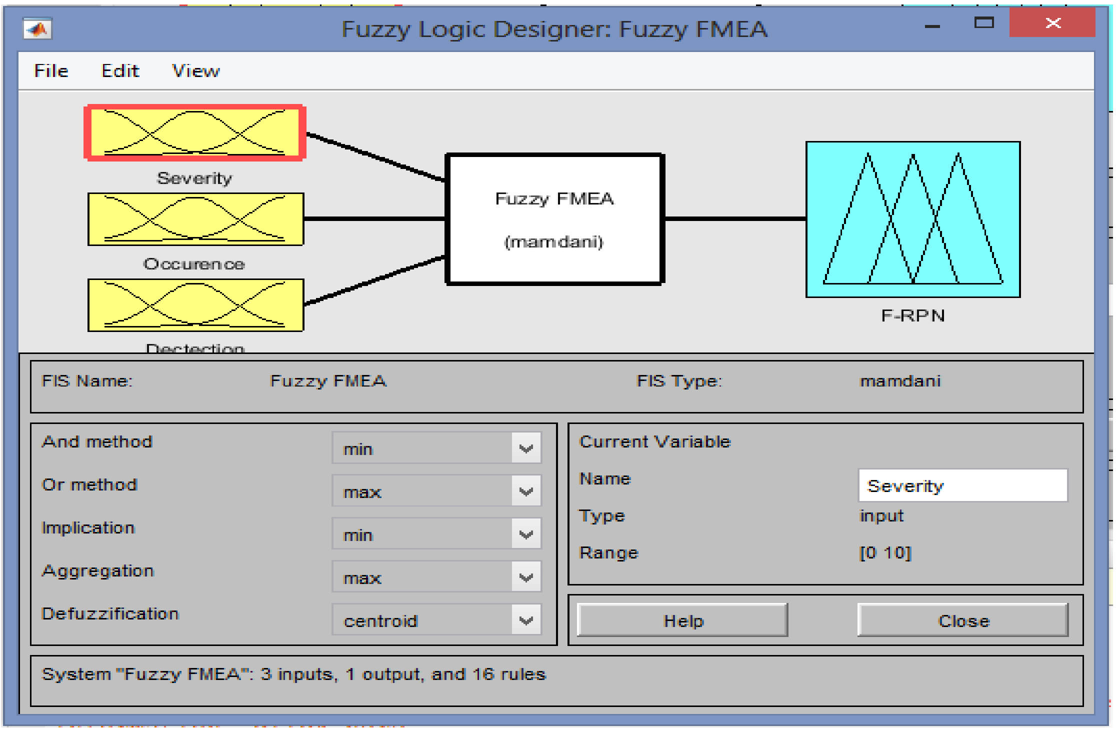


Figure 6.33 (a) FIS editor for selection of the type of curve of study area-1

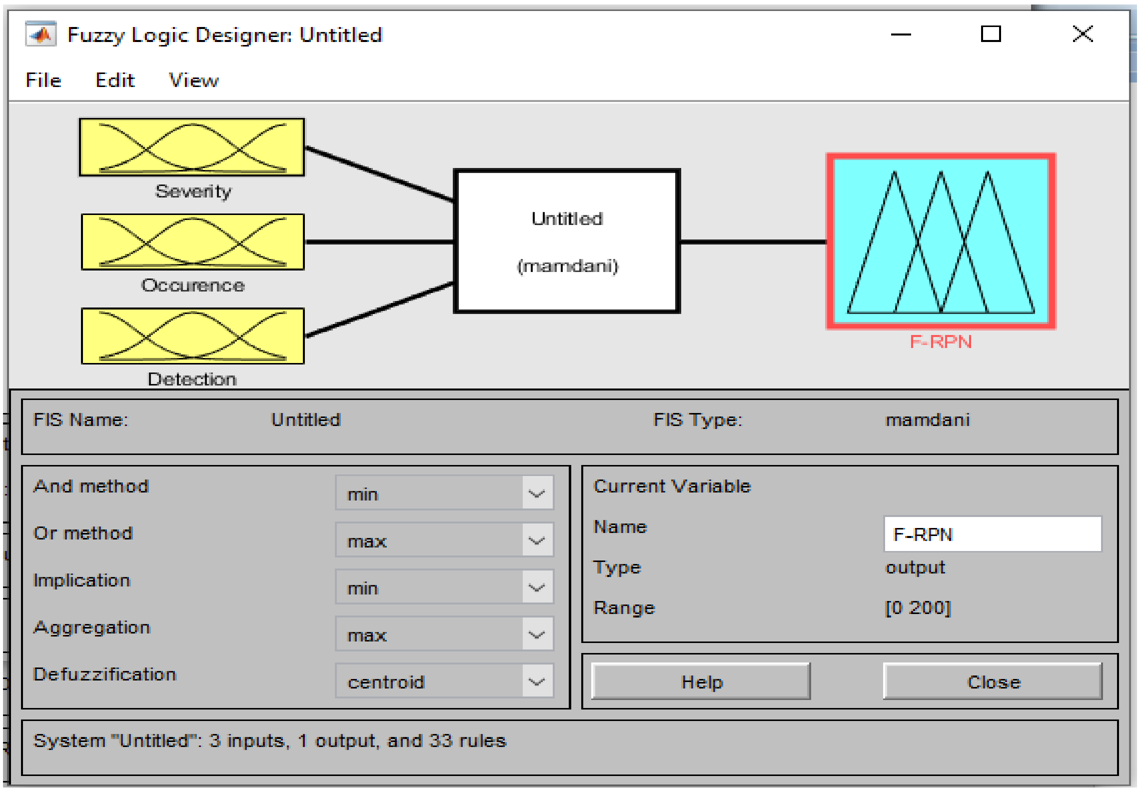


Figure 6.33 (b) FIS editor for selection of the type of curve of study area-2

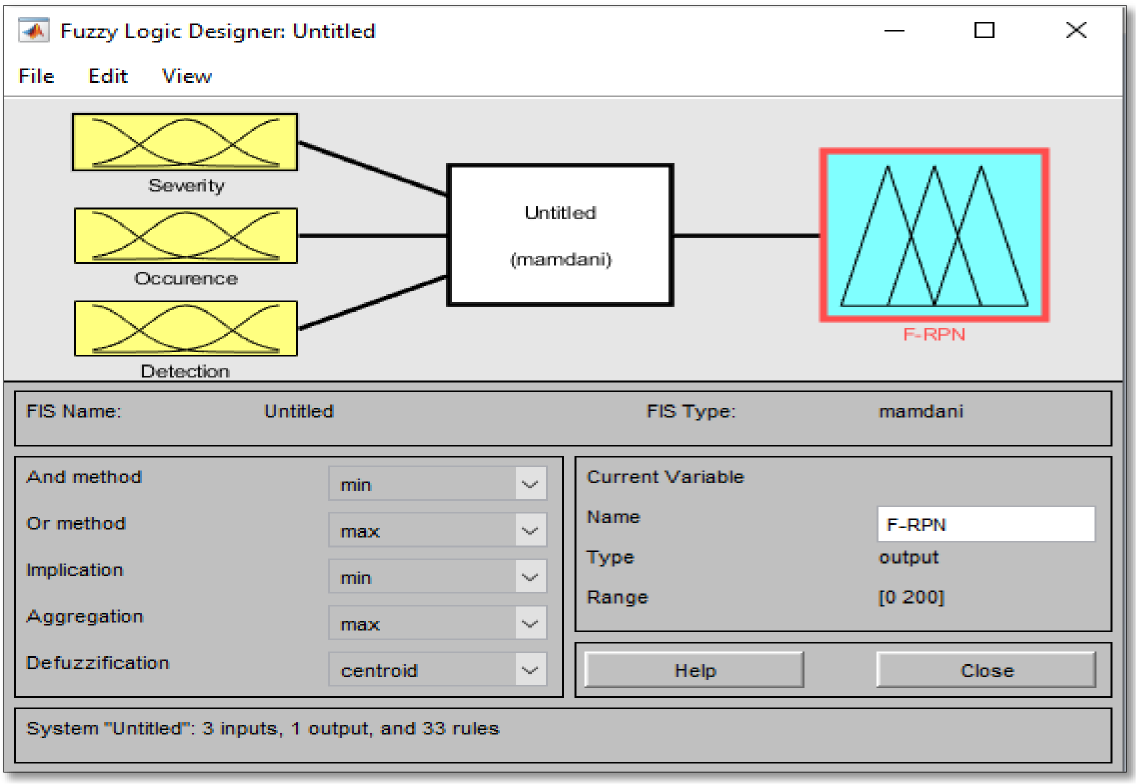


Figure 6.33 (c) FIS editor for selection of the type of curve of study area-3

- **Input Variables**

The input variables such as Severity, Occurrence and Detectability are determined in the membership function for study areas of 1, 2 and 3 (Figure 6.34 (a), (b) and (c)). The term ‘Severity’ describes the severity/risk/hazard level of the failed part/component. Under the level of significance, severity ranking should be allotted in a 1 to 10 point scale. The level in the severity scale can be estimated based on the familiarity and proficiency of the FMEA specialist. Occurrence is the probability of an exact failure that happened during a considered period. This can be estimated based on the frequency of the occurrence of a breakdown. Occurrence ranking is also given a severity ranking using a 1 to 10 point scale. The value 10 represents the highest probability of occurrence and similarly, 1 is the lowest probability of occurrence. Detectability defines the likelihood of the detection of a failure mode and it can also be expressed as the ability of a person to detect the potential breakdown mode and its consequence (V. R. Rengith and Dilip Madhavan 2018). Detectability can also be estimated using a 1 to 10 point scale. The lowest value of detectability can be assigned when there is no current control action for the failure mode. These parameters can be used to estimate the risk priority number (RPN). The criticality of the component can be decided based on the prioritization of a failure mode (Zadeh, L. A and Desoer, C. A 1965).

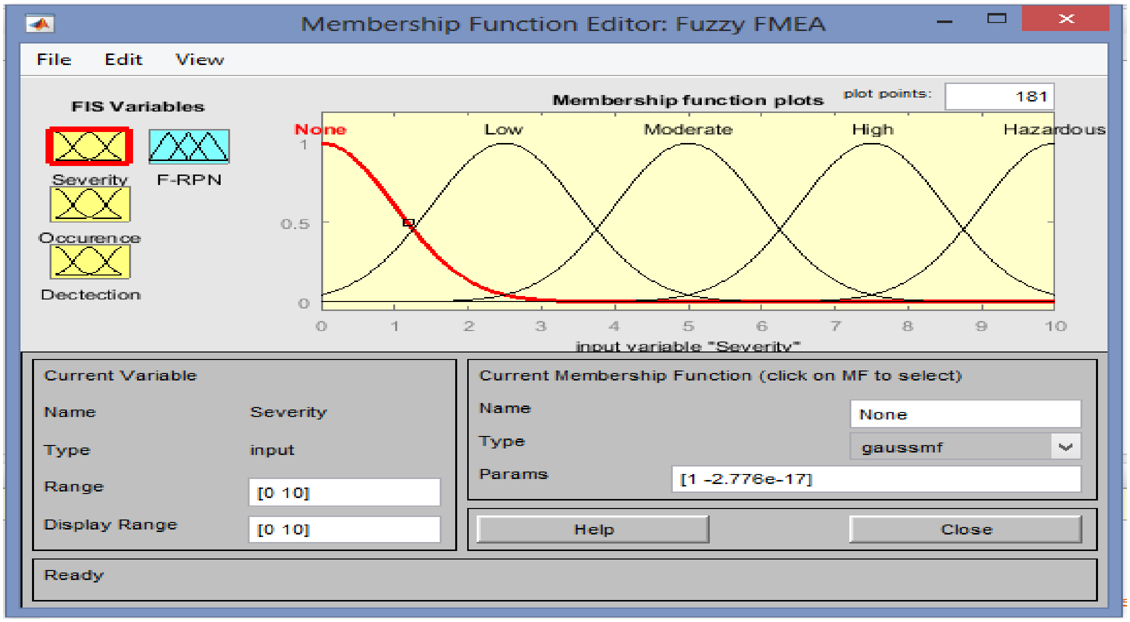


Figure 6.34 (a) Membership function editor of study area-1

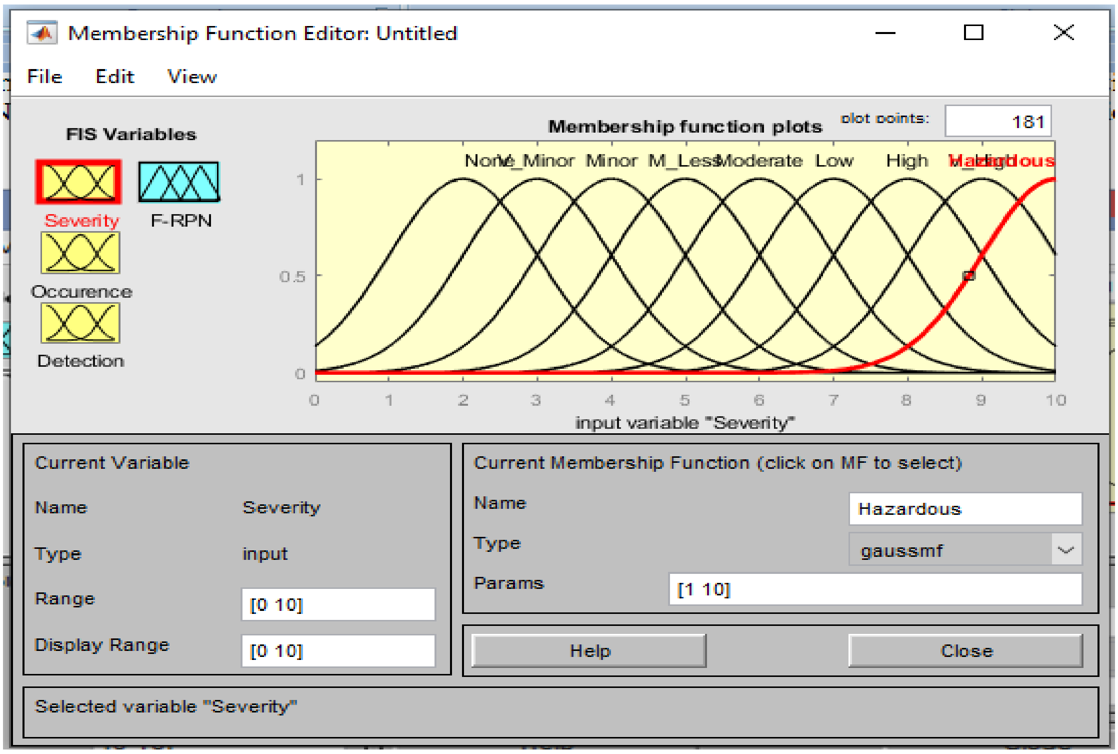


Figure 6.34 (b) Membership function editor of study area-2

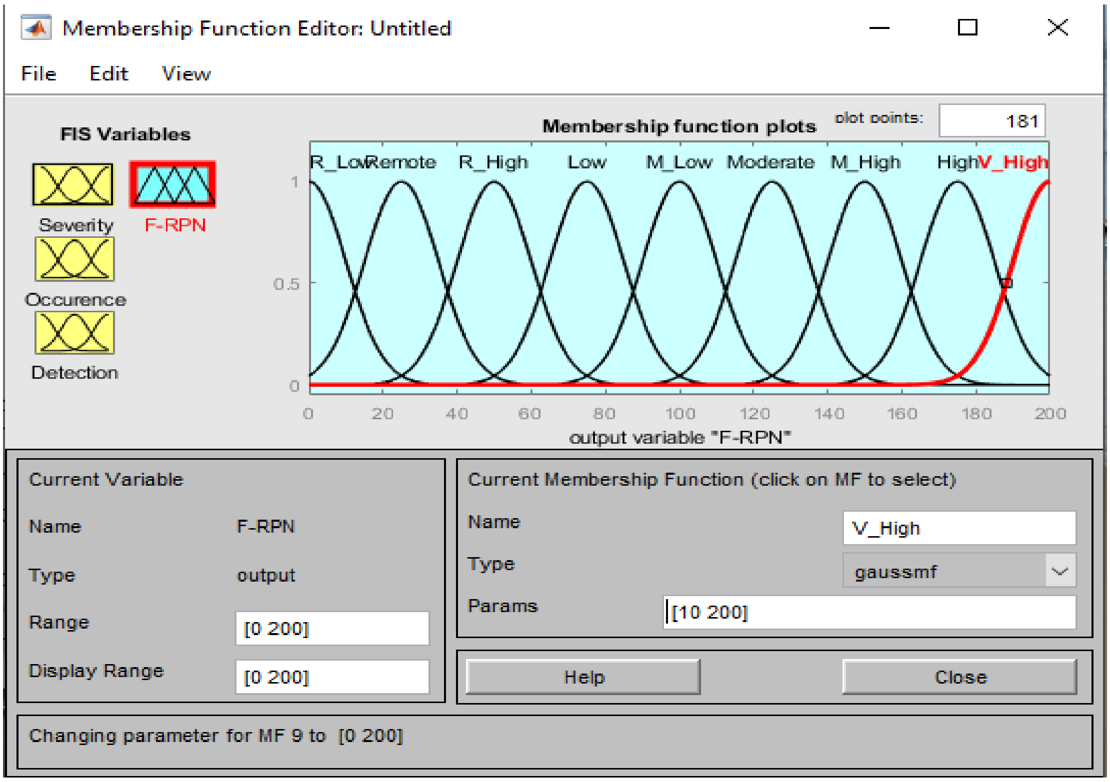


Figure 6.34 (c) Membership function editor of study area-3

- **Rule Editor and Rule Viewer**

The Rule Editor is a MATLAB-based logic unit which helps to add the rules in a linguistic form. The dependency of the output parameter should be dependent upon the given linguistic format input data. The training process was performed in MATLAB based fuzzy analysis for the created combination of input rules in study area-1(Figure 6.35 (a)). Similarly, training process screenshots of study area-2, 3 are shown in Figure 6.35 (b), (c).

'Rule viewer' is generally used to exhibit the image of the response in the MATLAB Fuzzy interface system. It is also used to demonstrate how the rules are fuzzified and how the individual membership function shapes are influencing the results of study area-1 data sets, as shown in Figure 6.36 (a). Similarly, the rule viewer for identification of fuzzified rules of study area-2 and 3 are shown in Figure 6.35 (b), and (c).

- **Rule Viewer and Surface Viewer**

The Surface viewer helps to view the dependency of the output on one or two of the inputs, such as Severity, Occurrence and Detection, for study area-1 is shown in Figure 6.37 (a) (V. R. Rengith and Dilip Madhavan 2018). Similarly, the surface viewer for study areas-2 and 3 are shown in Figure 6.37 (b), and (c). In this analysis, the presented surface viewer is a three-dimensional mapping view with severity, detection and FRPN. From the plot, it was noticed that the maximum amount of dependency of FRPN (142) was obtained for the combination of severity (3) and detection (8) risk indexes.

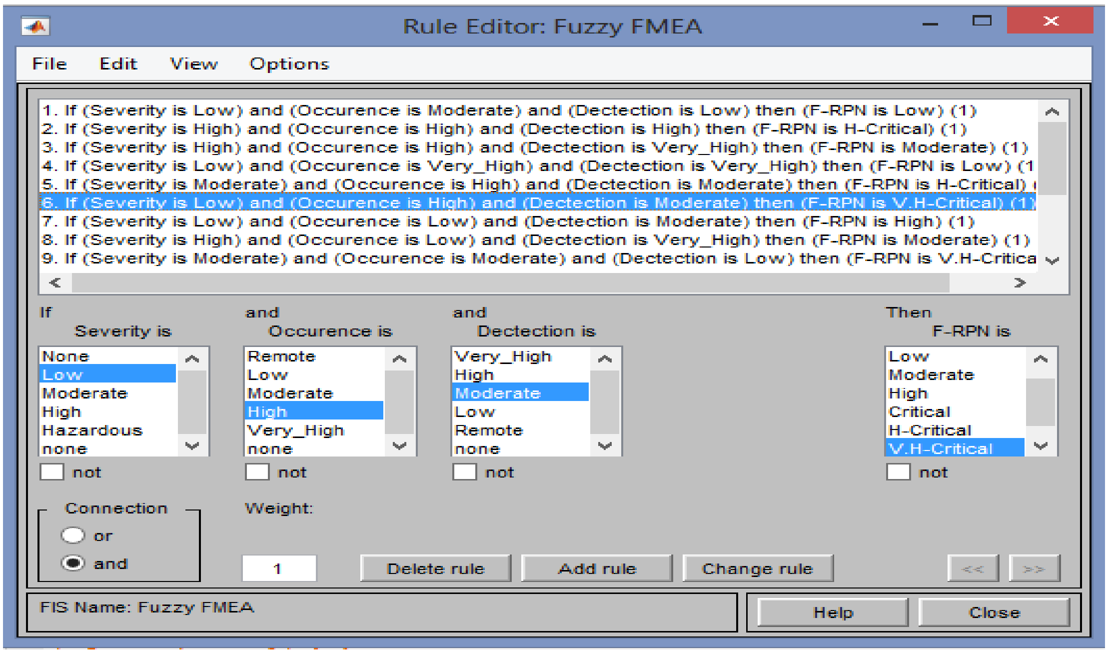


Figure 6.35 (a) Rule editor for the training process of study area-1

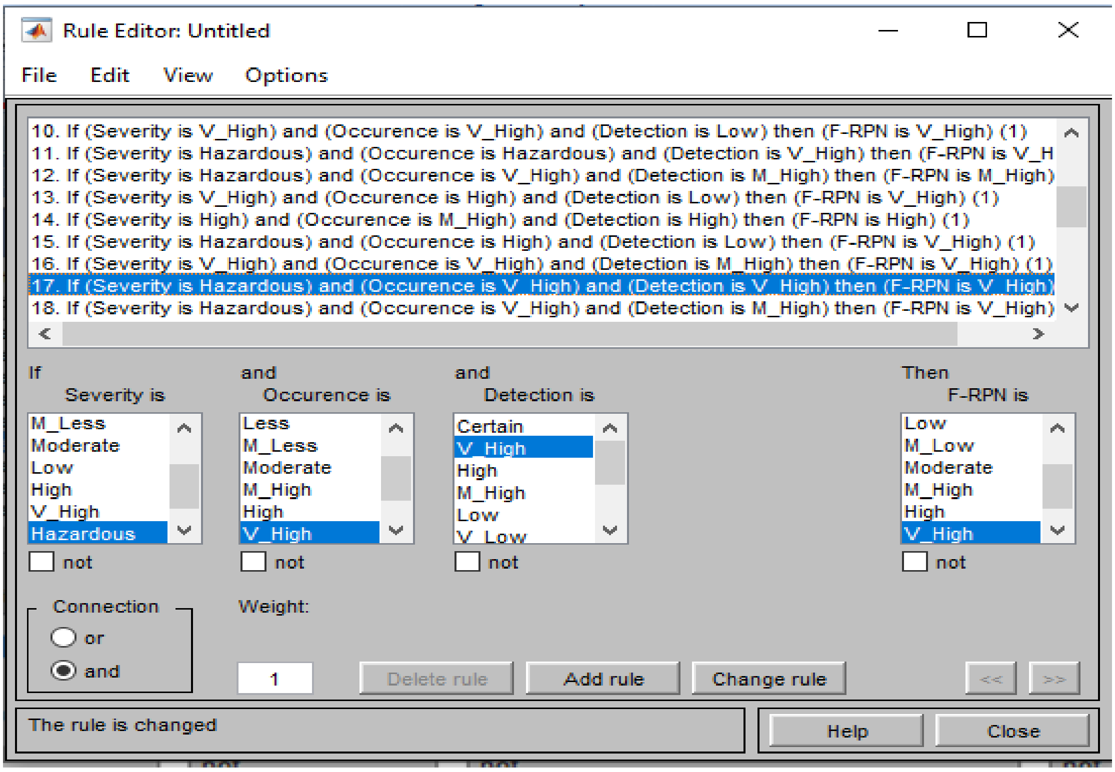


Figure 6.35 (b) Rule editor for the training process of study area-2

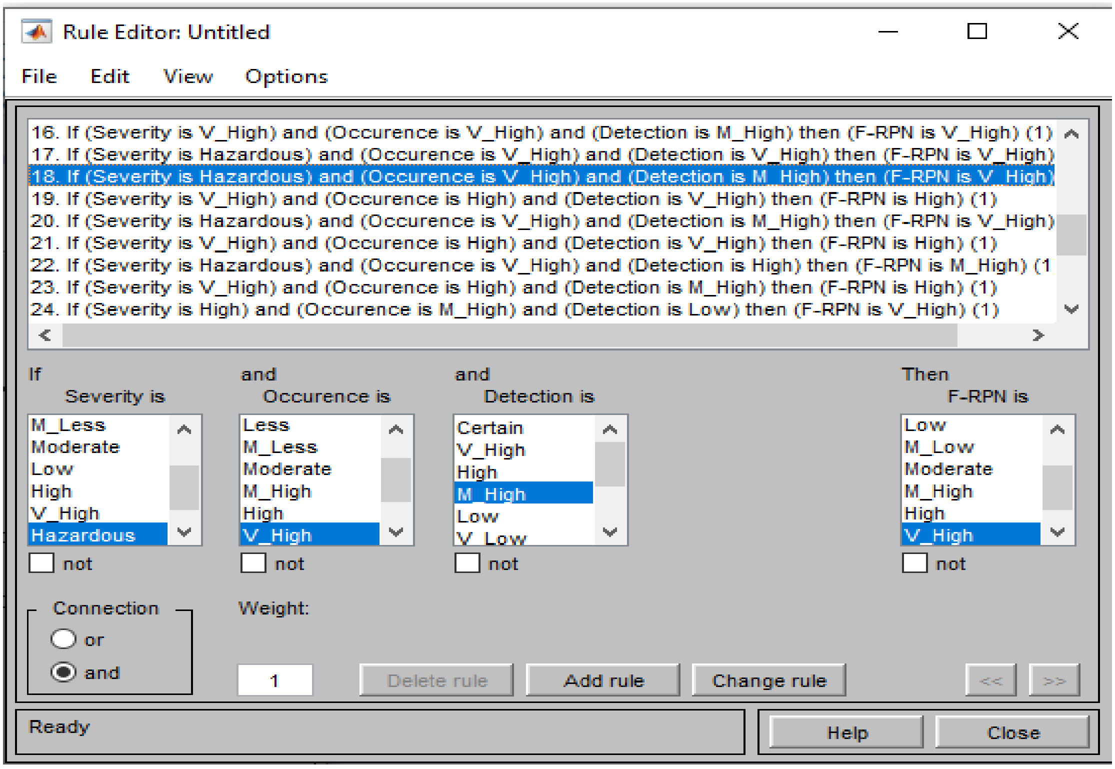


Figure 6.35 (c) Rule editor for the training process of study area-3

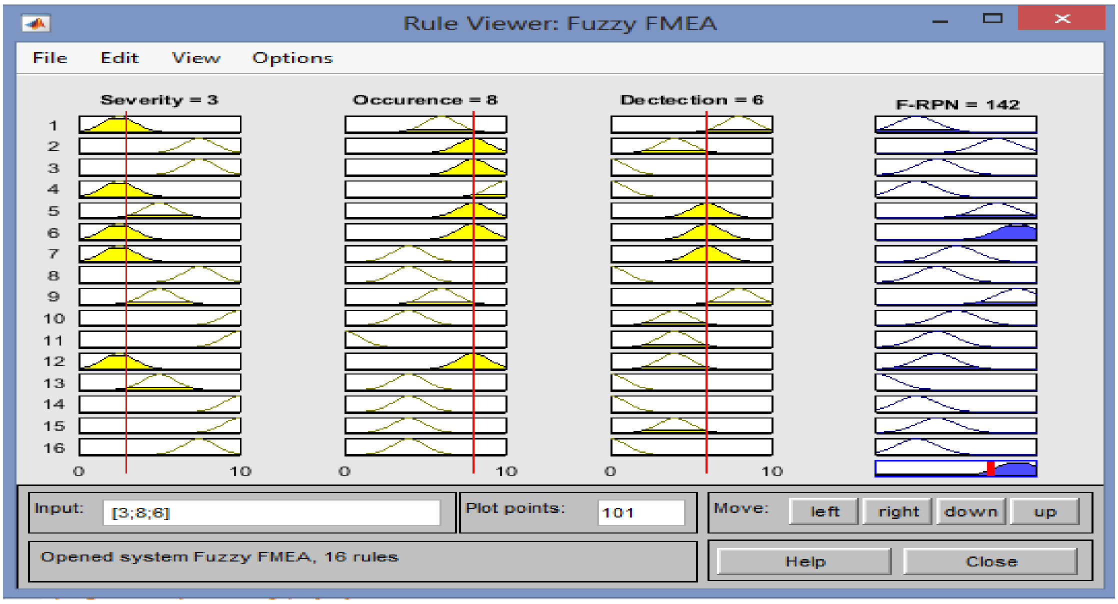


Figure 6.36 (a) Rule viewer for identification of Fuzzyfied rules of study area-1

Figure 6.36 (b) Rule viewer for identification of Fuzzyfied rules of study area-2

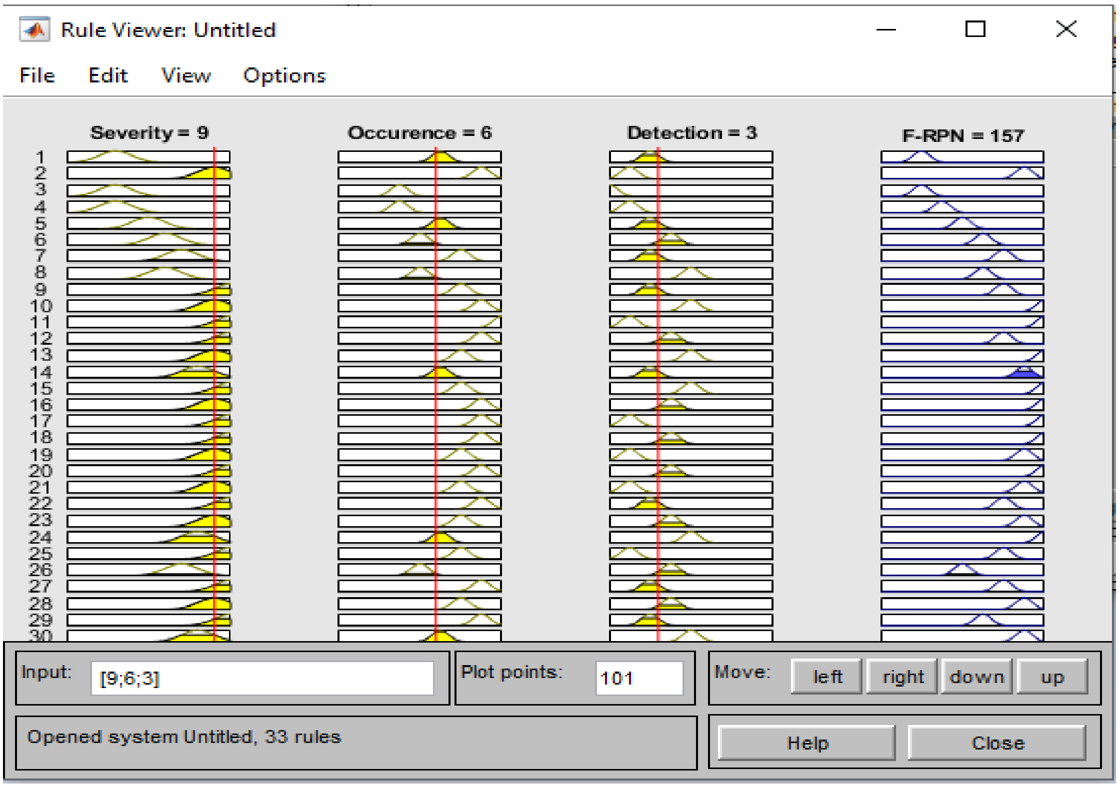


Figure 6.36 (c) Rule viewer for identification of Fuzzyfied rules of study area-3

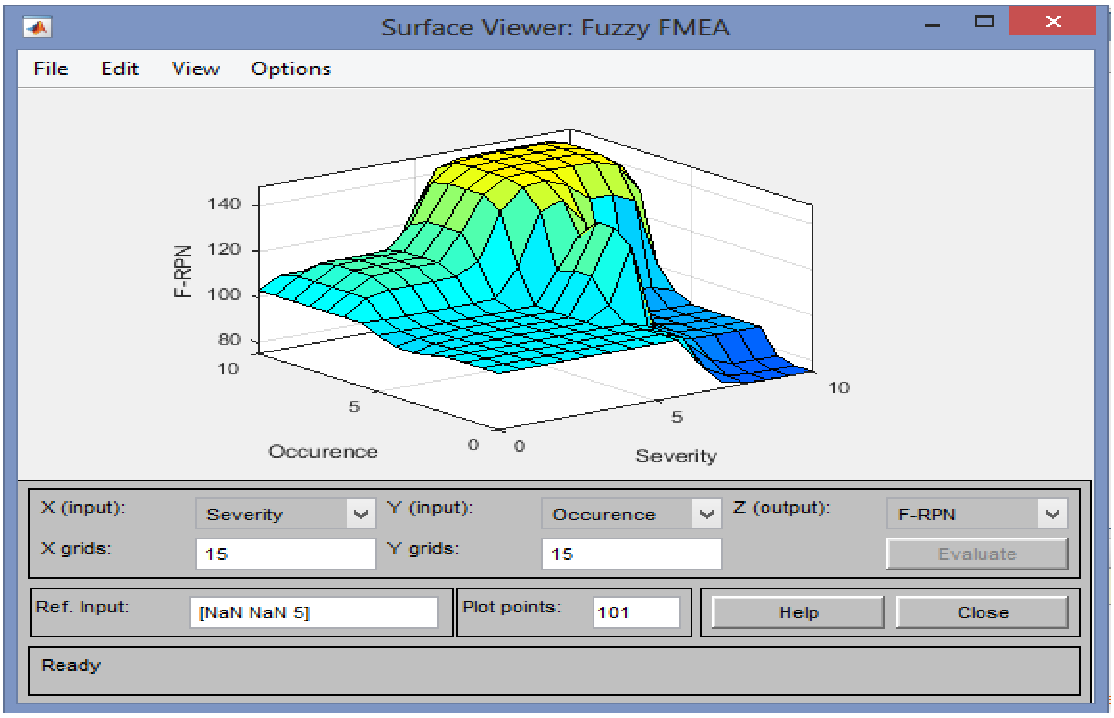


Figure 6.37 (a) Surface viewer of study area-1

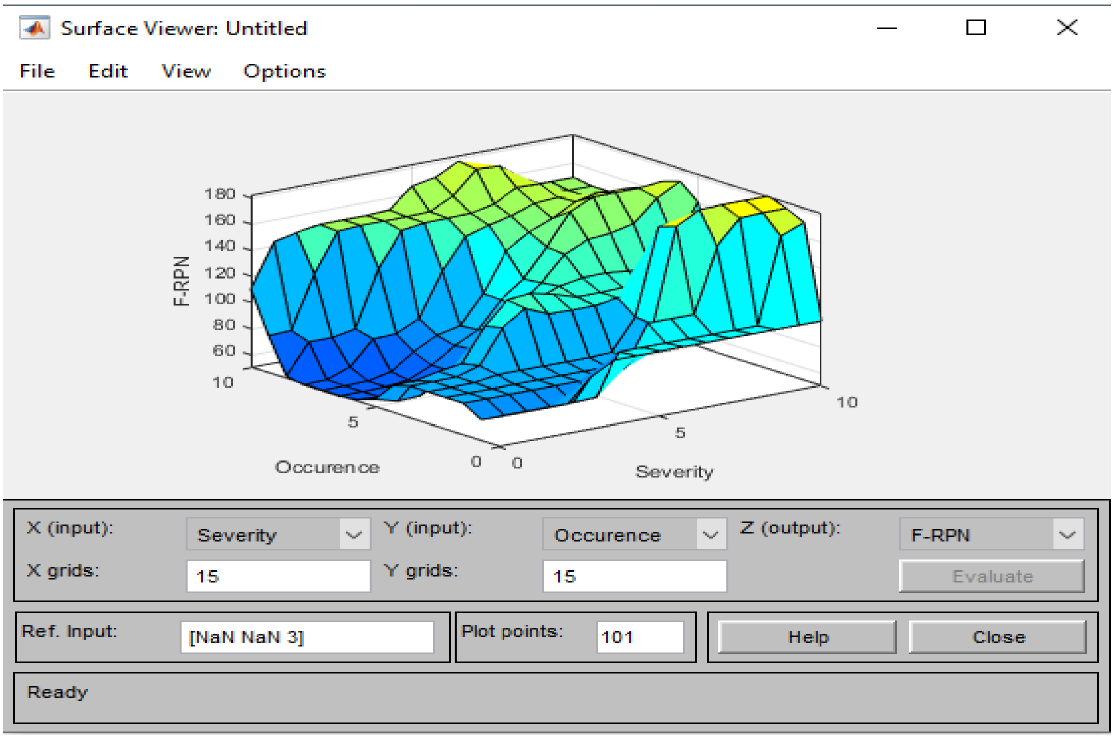


Figure 6.37 (b) Surface viewer of study area-2

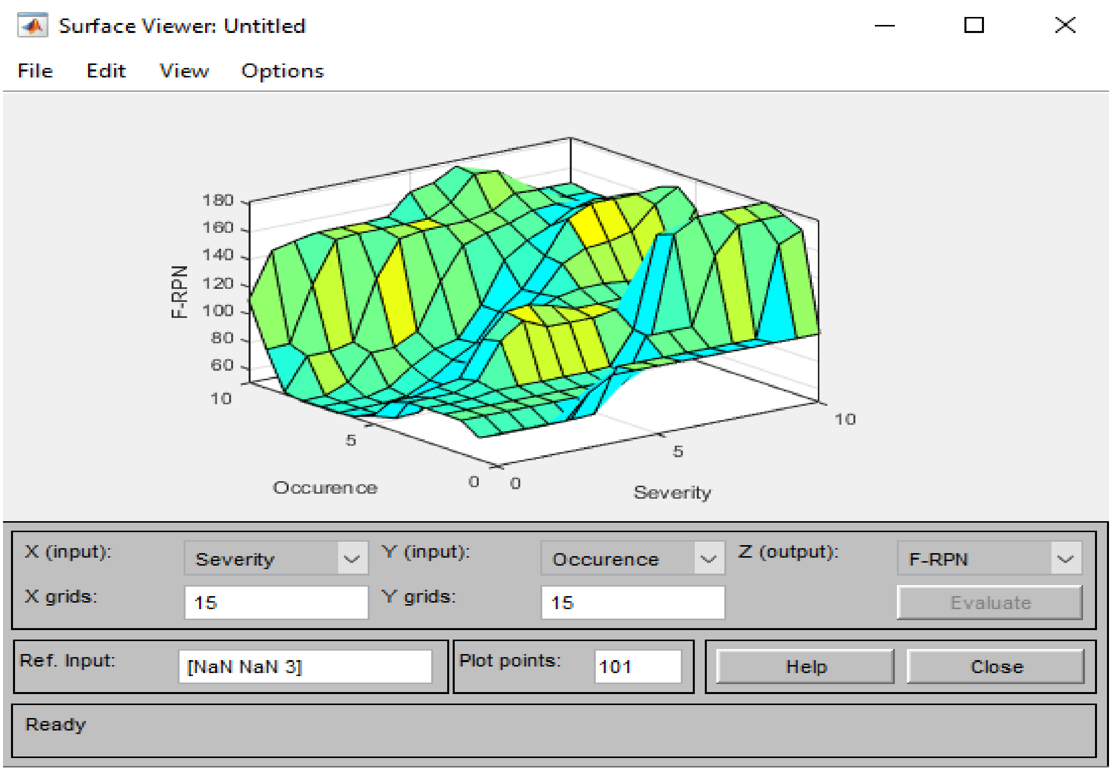


Figure 6.37 (c) Surface viewer of study area-3

6.2.5 Comparison of Conventional FMEA and Fuzzy FMEA Results

The analysis of priority ranking using conventional FMEA and Fuzzy based FMEA for the study area-1 analysis is given in Table 6.29. Similarly, for study area-2, 3 are given in Table 6.30, and Table 6.31. The prioritization of the failure modes or rankings of C-RPN and F-RPN was made based on computed RPN results. These were predicted by the product of risk indexed parameters such as S, O and D in the conventional FMEA approach. MATLAB based Fuzzy RPN results were obtained directly from the Fuzzy Interface System (FIS).

Table 6.29 Comparison of RPN results of study area-1

Sub-system	Failure Type	Conventional FMEA RPN	C-RPN Ranking	Fuzzy FMEA RPN	F-RPN Ranking
SSBr	F1	36	14	78.3	11
SSTy	F2	128	3	108	4
	F3	56	9	76.1	12
SSH	F4	36	15	67.6	15
	F5	144	2	142	1
	F6	96	4	142	2
	F7	48	12	93.7	5
SSE	F8	56	10	69.1	14
	F9	168	1	117	3
SSEl	F10	96	5	87.9	6
	F11	64	8	87.9	7
SSTr	F12	72	6	76.1	13
SSM	F13	20	16	32	16
	F14	54	11	80	8
	F15	72	7	80	9
	F16	48	13	80	10

Table 6.30 Comparison of RPN results of study area-2

Sub-system	Failure Type	Conventional FMEA RPN	C-RPN Ranking	Fuzzy FMEA RPN	F-RPN Ranking
SSE	F1	144	11	120	11
	F2	96	28	112	25
	F3	168	3	113.5	21
	F4	147	9	120	4
SSEl	F5	135	18	118	12
	F6	144	12	119	5
	F7	180	2	125	1
	F8	162	4	115	26
SSBo	F9	84	29	96.5	32
	F10	48	32	88.6	33
	F11	80	30	113	27
	F12	126	25	104	30
	F13	120	27	102.5	31
SSBr	F14	126	26	101	29
	F15	135	19	118	13
	F16	144	13	120	6
	F17	180	1	124.5	2
SSTr	F18	160	7	113	22
	F19	162	5	115	19
	F20	128	24	104	28
	F21	135	20	118	14
SSH	F22	162	6	115	20
	F23	144	13	120	7
	F24	140	17	118	15
	F25	147	10	124	3
SSTy	F26	135	21	118	16
	F27	144	14	120	8
	F28	160	8	113	23
SSM	F29	80	31	113	24
	F30	135	22	118	17
	F31	144	15	120	9
	F32	135	23	118	18
	F33	144	16	120	10

Table 6.31 Comparison of RPN results of study area-3

Sub-system	Failure Type	Conventional FMEA RPN	C-RPN Ranking	Fuzzy FMEA RPN	F-RPN Ranking
SSE	F1	180	1	198	1
	F2	96	24	104	25
	F3	126	17	111	20
	F4	144	7	152	7
	F5	162	3	157	3
	F6	84	25	96	26
SSEl	F7	135	11	138	15
	F8	144	8	152	8
	F9	36	29	62.5	28
	F10	70	28	86	27
	F11	36	30	62.5	29
	F12	112	20	106	24
SSBr	F13	84	26	96	30
	F14	135	12	138	11
SSTr	F15	128	16	111	21
	F16	135	13	138	12
	F17	160	6	157	5
	F18	162	4	157	6
SSH	F19	140	10	146	9
	F20	120	18	118	18
	F21	100	22	110	23
	F22	168	2	160	2
	F23	105	23	125	17
SSTy	F24	135	14	138	13
	F25	144	9	140	10
	F26	120	19	118	19
SSM	F27	80	27	90	24
	F28	162	5	161.5	4
	F29	135	15	138	14
	F30	108	21	125	16

From the results of the Fuzzy interface system for study area-1 (Table 6.29), it was understood that Fuzzy-FMEA is more accurate than the conventional FMEA. The failure modes of the system was prioritized based on the criticality/RPN value. In this observation, a similar kind of ranks (i.e.,1, 2, 8, 16,11) were noticed for the failure modes F9, F5, F11, F13 and F14. Likewise in study area-2 (Table 6.30), similar kind of results were noticed for the failure modes F1, F4, F6, F16, F23, F27, F31, F33, with F-RPN value 120, and F5, F15, F21, F24, F26, F30, and F32 with F-RPN value 118. For study area-3 (Table 6.31), similar kind of results was noticed for the failure type F5, F17, F18 with F-RPN of 157, F4, F8 with F-RPN of 152, F3, F15 with F-RPN of 111, and F16, F24, and F29 with F-RPN value of 138. The primary rank 1 can be assigned to the maximum RPN value and remaining values were also ranked accordingly. These sub-systems are named as critical sub-systems and more concentration needs to be kept on particularly on these critical parts. Hence, it was suggested that the highest value of RPN needs to be minimized by undertaking necessary modification or repair actions to improve the life of the equipment. In some cases, replacement of the component may also be required when the failed part is not possible to repair at the time of Preventive Maintenance. These failures are called censored failures and these can be replaced at the time of Corrective Maintenance (CM) with newly strengthen the design. It was concluded that this study i.e. fuzzy logic-based analysis not only determines the restrictions connected with a conventional approach for RPN, estimation of breakdown causes in reliability analysis of a complex repairable system but also presents additional benefits. In addition to that, the fuzzy rule base can also be amended or updated when there is an existence of more failure information. As a result, the proposed evaluation process will be constantly enhanced.

In the next chapter an attempt has been made to identify the current status of a machine by performing Overall Equipment Effectiveness (OEE) analysis. OEE is an effective metric for identifying losses, bench-marking progress and improving the productivity of an equipment. By measuring OEE and underlying losses, important insights were gained on how to systematically improve the effectiveness of an equipment.

CHAPTER-7

OVERALL EQUIPMENT EFFECTIVENESS (OEE)

This chapter explains the methodology of evaluating Overall Equipment Effectiveness (OEE) of the system with details of Key Performance Indicators (KPIs) and validation/ comparison with world-class standards comparison for performance assessment.

7.1 OVERALL EQUIPMENT EFFECTIVENESS (OEE)

Because of the highly competitive business environment, production facilities across all sectors of the industries are actively looking for the improvement of their assets and enhancing the quality of products/services. Various approaches to increase productivity, reduce costs and improve quality are being actively explored to achieve maximum efficiency in all dimensions (Aswin, Joseph and Jayamohan, M. S 2017). The productivity of LHD’s is primarily governed by parameters such as machine capacities and capabilities, hauling distances, operator skill; levels of preventive and predictive maintenance and the operational gradient, etc among many other parameters. The esoteric significance of the term productivity is “very case-specific” and its variation depends on specific site conditions. In general, every mining project starts with its production target rates. To reach these targets, the management attempts to maximize the utilization of its men and machinery (Paterson. W and Knights. P 2012). The productivity of LHD’s is a function of cycle time, which further depends on load/dump time, the capacity of bucket, haulage distance, grade speed, mine layout, road surface condition, etc. The availability of adequate energy infrastructure is another important consideration for the operation of the equipment. In the case of electric/diesel operated LHD’s infrastructure such as backup generators, storage tanks, refuelling stations and piping, it could be required (Praveen. Singh. Sisodiya 2014). One of the common approaches recommended for assessing the performance of LHD's is OEE. This is a well-defined technique for evaluating machine performance with an adequate level of confidence.

The concept of OEE is becoming increasingly popular and has been widely used as a quantitative tool, essential for the measurement of production (Huang et al. 2003). The OEE measurement is central to the formulation and execution of a Total Productive Maintenance (TPM) improvement strategy (Dhillon. B. S 2008). The literature reveals OEE as an equipment efficiency improvement tool. The objective of OEE measurement in a manufacturing company is to enhance the equipment and plant reliability by eliminating all the losses incurred. In this study, a methodology is presented for analysis of the OEE of LHD machines. Further, an approach is developed to identify and address the losses and failures, which are responsible for lowering the OEE. Wang, L. X. (2008) has concluded that the OEE metric can be used as an indicator of the reliability of the production system. A comparison of the gap between the expected and current OEE measurements has provided manufacturing organizations with a tool to improve the maintenance policy. OEE is a powerful tool, which helps to identify the areas of improvement regarding availability, performance rate and quality rate of products by classifying them into six major losses (Ram Prasad Choudhary 2015).

7.2 OVERVIEW OF OEE

The major goal of the TPM is to maximize the effectiveness of overall equipment. OEE is considered as the most efficient and effective tool (McKone. K. E et al. 1999) for driving plant improvement and it continuously focuses the plant on the concept of “zero waste”. The six major losses that result in lowering the OEE are discussed in this study and the elimination of these losses is the major objective of the TPM, as represented in Figure 7.1. The elimination of these losses may result in a dramatic improvement in Overall Equipment Efficiency (OEE). The calculation of OEE is performed by obtaining the product of availability of the equipment, performance rate of the process and rate of quality of products (Muchiri. P and Pintelon. L 2008) and (Nakajima. S 1989b), which may be expressed as (Equation 7.1):

$$\text{OEE} = \text{Availability (A)} \times \text{Performance rate (P)} \times \text{Rate of Quality (Q)} \qquad (7.1)$$

OEE provides a systematic method for establishing production targets and incorporates practical management tools and techniques to achieve a balanced view of process availability, performance efficiency, and rate of quality.

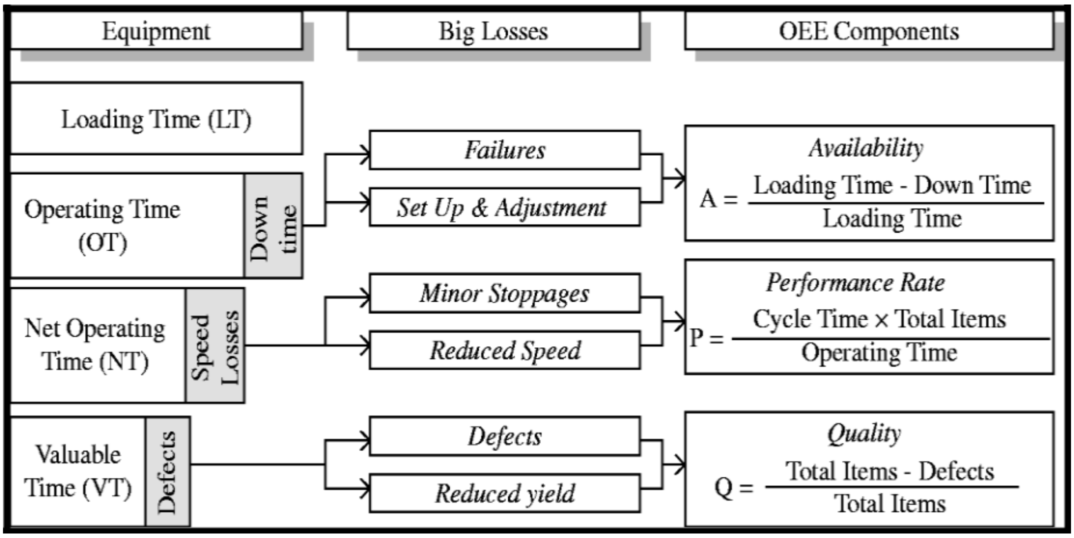


Figure 7.1 Six equipment losses and OEE (Yunos. Bin. Ngadiman et al. 2013)

OEE is a measurement tool used to evaluate equipment performance and to ensure permanent productivity improvement. The percentage of OEE is mainly dependent upon the effectiveness of three indices such as availability, performance rate, and quality. Although OEE has been developed from the base of TPM, proper maintenance and organization of TPM is required to obtain the OEE's benefits (Hansson. Al-Chalabi et al. 2014). OEE is not a technique that seeks to ensure that all equipment should operate at 100% efficiency. An overall 85 percent benchmark of OEE is considered as "world-class performance". A primary objective of TPM is to eliminate or minimize all such losses related to the manufacturing system to improve overall production effectiveness. In the initial stages, TPM initiatives majorly focus upon addressing six major losses, which are considered significant in lowering the efficiency of the production system (OEE Standard. 2012).

7.3 MEASUREMENT OF OEE

To calculate or measure the performance of underground mining equipment, OEE is an important indicator or metric. However, its significance for machinists will be very low unless OEE components are deliberated and evaluated more effectively than the regular measures (Paraszczak. J. 2005). The value of OEE is calculated in two different ways. One is production-related, which deals with produced output concerning the anticipated targets. The alternative approach is time-related, wherein, data related to working hours, breakdown hours, etc. is collected and utilized for evaluation of OEE. From the basic information or collected data, such as shift scheduled hours, maintenance hours, breakdown hours, idle hours, etc, the availability and utilization percentages, production index rate and overall equipment effectiveness can be determined. In this study, time-based factors were used to estimate the OEE value. The following relationships can bring the importance of these time-based factors:

- **Availability (A)**

Availability is one of the important measures in OEE analysis. It can be measured by downtime losses (Equation 7.3), which includes any events that stop planned production for an appreciable length of time known as "breakdown time" and "idle time" such as machine failures, spare part shortages, and change over time, etc. Complete elimination of change over time is not practically feasible but it can be reduced/minimized in many cases. The remaining available time is called "operating or working time" (Jardine. A. K. S. 1998).

$$\text{Availability(A)} = \frac{\text{Total Available time} - \text{Down time losses}}{\text{Total Available time}} \times 100 \qquad (7.2)$$

$$= \frac{\text{SS hr} - \text{BDhr} - \text{SM hr}}{\text{SShr}} \times 100 \qquad (7.3)$$

Where SShr is the shift scheduled hours, BDhr is the breakdown hours and SMhr is the scheduled maintenance hours.

- **Performance Rate (P)**

Performance can be calculated by accounting for speed losses (Equation 7.5), which includes scheduled maintenance hours, breakdown hours and idle hours. The balance available time of the machine is calculated as:

$$\text{Performance(P)} = \frac{\text{Operating time} - \text{Speed losses}}{\text{Operating time}} \times 100 \qquad (7.4)$$

$$= \frac{\text{SS hr} - \text{SMhr} - \text{BDhr} - \text{IDhr}}{\text{SShr}} \times 100 \qquad (7.5)$$

Where IDhr denotes idle hour.

- **Quality (Q)**

Providing quality products/services in any sector is of paramount importance for the success of any undertaking. It primarily refers to achieving “zero defects” status for those products. These may require additional re-working. Hence, the balance hours are called “completely useful period”. We aim to exploit these hours, (Jacobs, W. 2014) and the metric of quality was computed from Equation 7.7.

$$\text{Quality (Q)} = \frac{\text{Operating time} - \text{Defect losses}}{\text{operating time}} \times 100 \qquad (7.6)$$

$$= \frac{\text{SA hr} - \text{BDhr}}{\text{SAhr}} \times 100 \qquad (7.7)$$

Where SAhr denotes scheduled available hours

OEE is primarily a technique that will help to determine the equipment’s effectiveness. It explains the most regular and significant sources of productivity loss. Assessment of losses is utilized for evaluating machine availability, performance or percentage utilization and quality to evaluate the value of OEE. After factors such as availability, performance and quality are taken into account the overall equipment effectiveness is expressed as a percentage and is evaluated from Equation 7.1. The classified data of study area-1 for the present OEE study is given in Table 7.1. Similarly, the classified data of LHDs of study area-2 and 3 for OEE estimation are given in Table 7.3 and Table 7.5 (Appendix-2).

Table 7.1 Classified data of machinery of study area-1 for OEE analysis

Machine	**SShr**	**SMhr**	**SAhr**	**BDhr**	**MAhr**	**IDhr**	**MWhr**
LH21	17544	167	17377	2180	15197	2873	10144
LH22	17544	417	17127	1716	15411	405	13290
LH24	17544	273	17271	2308	14963	948	11707
LH25	17544	526	17018	1755	15263	151	13357
LH26	17544	340	17204	1931	15273	551	12791
LH27	17544	391	17153	1582	15571	233	13756
LH28	17544	467	17077	1685	15392	190	13517
LH29	17544	308	17153	1582	15571	233	13756
LH30	17544	219	17325	942	16383	966	14475
LH31	17544	468	17076	897	16179	686	14596

From the collected and classified data, contributing factors of OEE such as availability, performance rate and quality for respective LHDs are calculated based on time. After analyzing the performance of equipment, a comparison is made to identify the variation in OEE values obtained with the world-class norms of OEE. Under ideal conditions, Nakajima (1988) has indicated the world-class standards of contributing factors for OEE must be more than 90.00% for availability, 95.00% for performance rate and 99.99% for quality rate. These levels of availability, performance rate, and quality rate would result in an OEE of approximately 85.00%. If OEE is less than 85%, it indicates that considerable improvements in system/ sub-system performance are required (Nakajima. S. 1988). The performance of many of the machines is not satisfactory. The OEE of the 10 different machines (study area-1) from LH21-LH31 has been calculated and compared with world-class standards for identification of percentage of variation (Table 7.2). The computed and compared OEE metrics for study area-2 and 3 are given in Table 7.4 and Table 7.6 (Appendix-2).

Table 7.2 Computed and compared values of OEE of study area-1

Machine	**Estimated OEE Values**				**% Variation**
	% A	**%P**	**%Q**	**%OEE**	
LH21	86.62	70.24	87.45	71.07	13.57
LH22	87.84	85.53	89.98	67.6	17.04
LH24	85.28	79.88	86.64	59.02	25.62
LH25	86.99	86.13	89.69	67.19	17.45
LH26	87.05	83.91	88.78	64.84	19.8
LH27	88.75	87.42	90.78	70.43	14.21
LH28	87.73	86.65	90.13	68.51	16.13
LH29	89.22	87.89	90.78	71.16	13.48
LH30	93.38	87.87	94.56	77.58	7.06
LH31	92.21	88.30	94.75	77.14	7.5

From the computed results (Table 7.2), maximum availability percentage (92.21%) was observed for LH31 and a minimum was observed for LH24 (85.28%). Similarly, the performance rate was varying from 70.24% to 88.30% for all the machines. The maximum percentage of quality was observed for LH31 (94.75%) and the minimum for LH21 (87.45%). The OEE values were between 59.02% to 77.58% for LH21-LH31. Among all the machines, machine LH30 has given a bit better performance than others. However, an unsatisfactory level of OEE percentage was observed for each LHD system as compared with world-class standards of OEE (85.00%). This OEE percentage can be improved by undertaking “usability factors” in computation along with availability, performance rate and quality rate. The usability factor is defined as the ratio of running time to the operating time. The stop time losses are taken into account for the estimation of the usability factor. This modified OEE model can also establish a link for the reduction of six big losses such as equipment failure, adjustment and stoppage, idling, reduced speed, defects in process and operation, etc.

Similarly, for study area-2 maximum availability (97.56%) was observed for machine LHD-3 and the minimum was for machine LHD-1 (91.53%). The value of the performance rate ranged from 77.95% to 88.96% for LHD-1 to LHD-5. The value of the maximum percentage of quality was observed for LHD-3 (99.86%) and minimum for LHD-4 (95.22%). The percentage of OEE for all the machines in study area-2 was observed to be less than 85.00%. For study area-3 maximum availability (87.88%) was observed for machine E5-LHD5 and the minimum was for machine E2-LHD2 (68.30%). The performance rate ranged from 62.11% to 75.97% for E1-LHD1 to E6-LHD6. The maximum percentage of quality was observed for E3-LHD3 (99.54%) and minimum for E2-LHD2 (80.46%). The percentage of OEE for all the machines in study area-3 was observed to be less than 85.00%. The percentage deviation of OEE values with compared world-class standards of OEE values for study area-1 is shown in Figure 7.2. Similarly, for study area-2 and study area-3 are shown in Figure 7.3 and Figure 7.4 (Appendix-2).

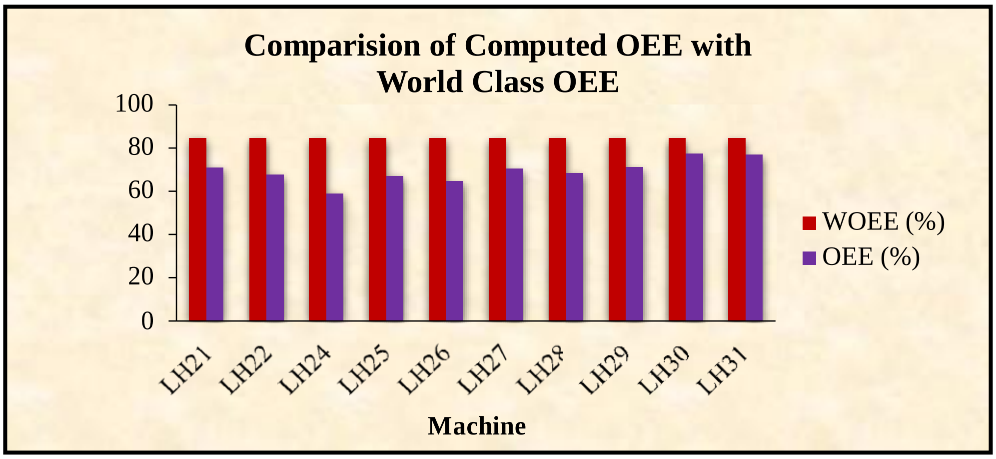


Figure 7.2 Comparison chart of OEE of study area-

CHAPTER-8
CONCLUSIONS AND FUTURE SCOPE

8.1 CONCLUSIONS

The present RAM analysis has given us an insight into several aspects of LHD working conditions, reasons for the occurrence of failures, influence of failure modes on its performance and reliable life. Significant results from the investigations carried out are:

- In respect of study area-1, from the results of KPIs, machine LH21 (80.67%) has the highest availability percentage as compared with others. Even though the machine was having the highest availability percentage, it was not utilized to the expected level, with a low utilization value of 56.25% only. Similarly, for study area-2, LHD-3 (97.56%), and study area-3, E5-LHD5 (87.88%) had the highest availability, and the corresponding utilization percentages are 76.72% (LHD3), and 44.60% (E5-LHD5) respectively. It is concluded that the unavailability of the machine in its working state and its in-effective utilization leads to a substantial reduction in production. This can be improved by strict adherence to Preventive Maintenance (PM) schedules, better organization of men and machinery, trained operating personnel and well-maintained equipment.

- From the reliability analysis, it was observed from study area-1 (Table 5.1 & Figure 5.7), that low levels of reliability were observed for sub-systems of SSH, SSTy, SSEl and SSTr ranging from 16.00% to 20.96%. Similarly, in study area-2 (Table 5.2 & Figure 5.9, Appendix-2) least value of reliability was noticed for SSBr (34.92%), SSEl (32.68%), and SSTr (44.61%), and in study area-3 (Table 5.3 & Figure 5.11, Appendix-2) least values of reliability were noticed for SSBr (22.34%), and SSTy (22.34). These low-reliability sub-systems are more critical as compared with others (SSBr, SSTr, SSH, SSEl and SSM). The reliability of a repairable system is mainly a function of its design, operation and maintenance credentials. Hence, it indicates that more concentration needs to be placed on these sub-systems, and implementation of the necessary repair or replacement actions will improve reliability.

- From the results of RBD (Table 5.1 & Figure 5.8), overall system reliability was found to be maximum for LH21(69.11%), LH29(69.44%) and LH30(69.41%) and minimum for LH24(56.77%) and LH26(59.98%) in study area-1 as compared with other systems. Similarly, (Table 5.2 & Figure 5.10, Appendix-2), overall system reliability was found to be maximum for LHD3 (87.49%), and minimum for LHD1 (64.77%) in study area-2. Likewise, (Table5.3& Figure 5.12, Appendix-2), overall system reliability was found to be maximum for E3-LHD3 (88.09%), and minimum for E5-LHD5 (68.87%) in study area-3. Reduction in overall system reliability is due to frequent, and un-even occurrence of failures with fewer TBFs. To improve the system reliability "additional redundancy" can be incorporated by analyzing the components having high levels of frequency of failures, thereby providing alternative pathways for the accomplishment of the stated task. Hence, it is recommended that low efficiency equipment should be maintained to its expected level by designing the "optimal maintenance practices".

- From the estimated results of reliable life (T_R) of study area-1 (Table 5.4), it was understood that the reliable life of LH 21 was observed as 834.23 hours. Similarly, for study area-2 (Table 5.5, Appendix-2), the T_R of LHD1 was observed as 233.04 hours. For study area-3 (Table 5.6, Appendix-2), the T_R of E1-LHD1 was observed as 428.57 hours. After the completion of this period, a first failure is likely to happen. This can be improved by increasing the level of system reliability. It is recommended that the estimation of T_R must be carried out at the initial stage only to identify the early life failure. If this estimation is made at the commissioning stage, then the machine health condition will be under control.

- In respect of study area-1 (Table 4.22), the maintainability percentage was found to be maximum for LH27 (99.99%) & LH29 (99.99%) and minimum for LH21 (96.73%). Similarly, in study area-2 (Table 4.23, Appendix-1), the maximum maintainability percentage for LHD2 (99.98%) and minimum for LHD4 (96.48%). Likewise, in study area-3 (Table 4.24, Appendix-1), the maximum maintainability percentage for E1-LHD1 (99.89%) and minimum for E4-LHD4 (97.12%). Even though the machines are well maintained the performance of

LHDs is very low. Hence, it is concluded that the strict adherence to timely and effective maintenance actions of repair and replacement helps to make the machinery always available and ready for use.

- From the Preventive Maintenance (PM) results (Table 4.25), it was understood that if the requirement of reliability is 90% for LH21, the PM should be performed for every 538 hours, and similarly, for LH22 to LH31, they are 367, 349, 620, 288, 1072, 412, 870, 1257 and 673 hours respectively. Similarly, for study area-2 PM should be performed for LHD1 for every 70 hours and other systems are given in Table 4.26 (Appendix-1). For study area-3, PM should be performed for E1-LHD1 for every 38 hours and other systems are given in Table 4.27 (Appendix-1). The PM time schedules are used as the guidelines to carry out the periodic inspections for the equipment. Delay in carrying out of maintenance actions causes the occurrence of secondary damage of the components (internal failure of the directional spool in steering, rear axle drive shaft and lift cylinder piston bending in hydraulics, etc) resulting from the failure of any one of the sub-systems within a system. It is concluded that PM helps to keep or retain the equipment in a satisfactory level of the operating condition through periodic inspections, greasing and oiling of moving parts, replacement of worn-out parts, overhauling of the entire machine, etc.

- From the Isograph Reliability Workbench (IRW) results of FTA for study area-1 (Table 5.7), the maximum percentage of overall system availability (As) was observed for LH29 (79.51%) and minimum for LH24 (70.10%). Similarly, for study area-2 (Table 5.8, Appendix-2) LHD2 was maximum (91.02%), and LHD4 was minimum (84.22%) and for study area-3 (Table 5.9, Appendix-2) E5-LHD5 had maximum (88.18%) and E2-LHD2 had minimum (69.68%). From the Fussell-Vesely (FV) importance graphs (Figure 5.40 to Figure 5.45), it was noticed that the sub-system components such as Engine, Frame, Axle, electrical system and Tyre contribute more significantly to end gate failure. It is concluded that these influencing components can significantly contribute to the reduction of system availability, and should be considered as critical components. It is concluded that there is a need for conducting root cause (risk) analysis of failures for the identification of potential causes of critical failures.

- From the results of FMEA of study area-1 (Table 5.16), it was noticed that the highest RPN values were obtained for the sub-systems of SSTy (F2-128), SSH (F5-144), and SSE (F9-168). Similarly, the highest RPN values were obtained for study area-2 (Table 5.17, Appendix-2) in respect of SSE (F1-144, F3-168, and F4-147), SSEl (F5-135, F6-144, F7-180, and F8-162), SS Br (F16-144, and F17-180), and SS Tr (F18-160, and F19-162). The highest RPN values obtained for study area-3 (Table 5.18, Appendix-2) were for SSE (F1-180, and F5-162), SSTr (F16-160, and F17-162), SSH (F22-168), and SSM (F28-162). If the RPN value is high, then the effect of this failure mode is more critical, which reduces the useful life and corresponding reduction of mine production. It is concluded that RPN values serve as a guide in the prioritization of probable failure modes, to minimize the level of severity and failure occurrence. It will also be useful to identify or recommend the necessary actions for design or process modification.

- From the results of Fuzzy-FMEA of study area-1 (Table 6.29), the maximum Risk Priority Number (RPN) values were noticed for failure modes SSH-F5 (142), SSH-F6 (142), SSE-F9 (117), SSTy-F2 (108) and SSH-F7 (93.7). Similarly for study area-2 (Table 6.30), the maximum RPN values were noticed for failure modes SSEl-F7 (125), SSBr-F17 (124.5), SSH-F25 (124), SSEl-F6 (120) and SSEl-F6 (119). Likewise, for study area-3 (Table 6.31), the maximum RPN values were noticed for failure modes SSE-F1 (198), SSH-F22 (160), SSE-F5 (157), SSM-F28 (161.5) and SSTr-F17 (157). In prioritization of RPN, ranking 1 can be assigned to the largest value of RPN and can be treated as most probable critical failure mode. Hence, it is concluded that more concentration/attention needs to be kept on critical components of SSH, SSE, SSTy, SSEl, SSBr, SSTr and SSM sub-systems. The necessary action plans must be formulated to control/reduce the likelihood of occurrence of potential failures and its severity level. The impact of the risk can only be reduced by reducing its RPN value, that means reducing either of the severity, occurrence or detection ratings.

- Computed LHD performance characteristics (Availability, Reliability, and PM) were validated with MATLAB based ANN predicted outputs. It was noticed that the obtained and predicted values of these characteristics with optimum R^2 value gives the best optimum results. The optimum R^2 values of developed availability, reliability and PM models have given satisfactory results. From the Figures 6.7, 6.8 and 6.9 of study area-1, 2 and 3, the maximum error between the predicted and computed results of availability was 9.94% for LHD3 (less than 10%). Similarly, from the Figures 6.16, 6.17 and 6.18 of study area-1, 2 and 3, the maximum error between the predicted and computed results of reliability are 12.38% for E1-LHD1 and 18.93% for E6-LHD6 (less than 20%). Likewise, from the Figures 6.25, 6.26 and 6.27 of study area-1, 2 and 3, the maximum error between the predicted and computed results of PM are 82.48 hours for LH28 and 21.49 hours for LHD1 (less than 100 hours). The computed and predicted results of availability, reliability and PM shows that the predicted results were found to be closer to the computed values, Indicating that the developed ANN is an appropriate model.

- From the results of OEE, Tables 7.2; 7.4 and 7.6 (Appendix-3), an unsatisfactory level of OEE percentage was observed for all the LHDs in all study areas-1, 2 and 3 as compared with world-class standards of OEE (85.00%). It is concluded that the estimation of OEE gives a “benchmark” for the identification of the gap and need for equipment performance improvement. This percentage can be improved through controlling the working place ambience and maintenance infrastructure-related (location and access) problems and by the improvement & strengthening of maintenance policy, spare parts inventory control policy, training policy, etc. to the maintenance and operating crew, etc.

8.2 RECOMMENDATIONS FOR FUTURE WORK

The main intention of the present research work is to study and analyze the performance of LHD machines in both coal and metal mines using reliability engineering techniques. This analysis provides a scientific basis for “optimal decision making” in maintenance policy, inventory policy, design philosophy/ modification, training policy, working place ambience, maintenance infrastructure-related (location and access) problems, etc to improve the equipment life as well as its performance.

Due to the limitation of time and availability of failure data sets of machinery, the present work is limited to forecasting the system reliability, availability and maintainability of LHDs, to identify the failure behaviour of the system and to identify the contributing factors/critical subsystems/components causing system failure. However, it may be further extended in the following points:

- In addition to the performance analysis, the development of Life Cycle Cost (LCC) models may be carried out to analyze productivity vis-à-vis economic relationships. Developed LCC models would provide the necessary information to the management for appropriate decision making.

- This thesis work presents the performance of manually operated LHD machines deployed in Indian underground mines. As the tele-operated (automated) LHDs are advantageous than manually operated machines, it is recommended that the performance evaluation process needs to be carried out for automated LHDs along with manual machines for identification of best operation mode between them. This analysis may describe the maintenance procedures and may identify the environmental disturbances affecting the system performance.

- The present study has not considered any of the operator-related parameters. A reduction in human-related problems can lead to an increase in equipment reliability and decrease the number of failures. A comprehensive study may be carried out on how “human factors” influence the performance of LHDs.

- A variety of “Condition monitoring sensors” such as embedded sensors (embedded fiber optic sensors), ultrasonic transmission sensors (piezoelectric and electrostrictive wafers), etc. may be applied on less reliable or critical sub-systems/components to measure the strain and to generate the ultrasonic energy to identify the critical time, just before failure is due. These may be helpful to detect the early life failure of the sub-systems, to identify the common failure modes, to initiate remedial action strategies of repair and replacement and to maintain the desired level of system reliability, availability and maintainability.

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APPENDIX-1

Table 4.2 TBF and TTR data sets of sub-systems of LHDs of study area-2

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LHD-1	FF (No/.)	13	8	21	15	19	11	18
	TBF (hours)	1615	2021	897	1614	1153	4046	1008
	TTR (hours)	153	190	87	155	111	376	98
LHD-2	FF (No/.)	11	7	20	8	32	7	24
	TBF (hours)	1340	2683	1338	2684	1003	4026	1340
	TTR (hours)	127	250	129	250	97	375	127
LHD-3	FF (No/.)	8	7	13	5	16	7	12
	TBF (hours)	2691	2017	1150	2690	731	2018	1151
	TTR (hours)	250	189	111	251	71	187	110
LHD-4	FF (No/.)	11	9	13	11	24	10	27
	TBF (hours)	1150	2012	1602	1342	665	2014	800
	TTR (hours)	111	194	163	129	70	192	82
LHD-5	FF (No/.)	8	7	15	7	16	9	16
	TBF (hours)	1627	2035	1027	1628	902	1356	1162
	TTR (hours)	132	164	87	131	75	110	94

Table 4.3 TBF and TTR data sets of sub-systems of LHDs of study area-3

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
E1-LHD1	FF (%)	12	9	21	10	25	8	32
	TBF (hours)	881	883	288	883	211	880	2012
	TTR (hours)	199	199	66	199	50	199	50
E2-LHD2	FF (%)	14	4	11	13	31	6	42
	TBF (hours)	644	979	558	341	259	785	155
	TTR (hours)	193	289	165	105	77	231	56
E3-LHD3	FF (%)	12	10	17	10	30	11	29
	TBF (hours)	845	1129	478	676	183	676	181
	TTR (hours)	145	194	83	116	32	116	34
E5-LHD5	FF (%)	13	8	24	10	37	6	40
	TBF (hours)	535	1254	264	940	202	1879	222
	TTR (hours)	70	164	35	123	27	247	31
E6-LHD6	FF (%)	11	10	16	11	39	8	37
	TBF (hours)	977	782	648	781	188	1307	215
	TTR (hours)	148	118	99	118	30	197	35

Table 4.5 Calculated values of CTBF, CTTR and CFF of study area-2

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LHD-1	CFF (No/.)	13	21	55	70	89	100	118
	CTBF (hours)	1615	3636	6552	8166	9319	13365	14373
	CTTR (hours)	153	343	622	777	888	1264	1362
LHD-2	CFF (No/.)	11	18	47	55	87	94	118
	CTBF (hours)	1340	4023	8042	10726	11729	15755	17095
	CTTR (hours)	127	377	758	1008	1105	1480	1607
LHD-3	CFF (No/.)	8	15	33	38	54	61	73
	CTBF (hours)	2691	4708	8548	11238	11969	13987	15138
	CTTR (hours)	250	439	801	1052	1123	1310	1420
LHD-4	CFF (No/.)	11	20	42	53	77	87	114
	CTBF (hours)	1150	3162	6104	7446	8111	10125	10925
	CTTR (hours)	111	305	599	728	798	990	1072
LHD-5	CFF (No/.)	5	9	22	27	36	42	49
	CTBF (hours)	1627	3662	6316	7944	8846	10202	11364
	CTTR (hours)	132	296	515	646	721	831	925

Table 4.6 Calculated values of CTBF, CTTR and CFF of study area-3

Machine ID	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
E1-LHD1	CFF (%)	12	21	52	62	87	95	127
	CTBF (hours)	881	1762	2624	3506	3716	4596	4797
	CTTR (hours)	199	398	597	796	846	1045	1095
E2-LHD2	CFF (%)	14	18	33	46	77	83	125
	CTBF (hours)	644	1623	3158	3499	3758	4543	4698
	CTTR (hours)	193	482	936	1041	118	1349	1405
E3-LHD3	CFF (%)	12	22	45	55	85	96	125
	CTBF (hours)	845	1974	3584	4260	4443	5119	5300
	CTTR (hours)	145	339	616	732	764	880	914
E5-LHD5	CFF (%)	13	21	55	65	102	108	148
	CTBF (hours)	535	1782	2678	3618	3820	5699	5921
	CTTR (hours)	70	234	351	474	501	748	779
E6-LHD6	CFF (%)	11	21	47	58	97	105	142
	CTBF (hours)	977	1759	3189	3970	4158	5465	5680
	CTTR (hours)	148	266	483	601	631	828	863

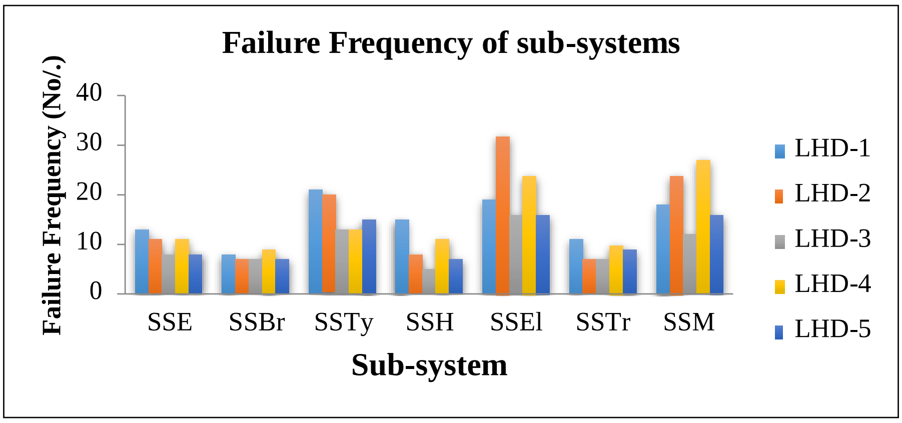


Figure 4.2 FF of sub-systems of LHDs of study area-2

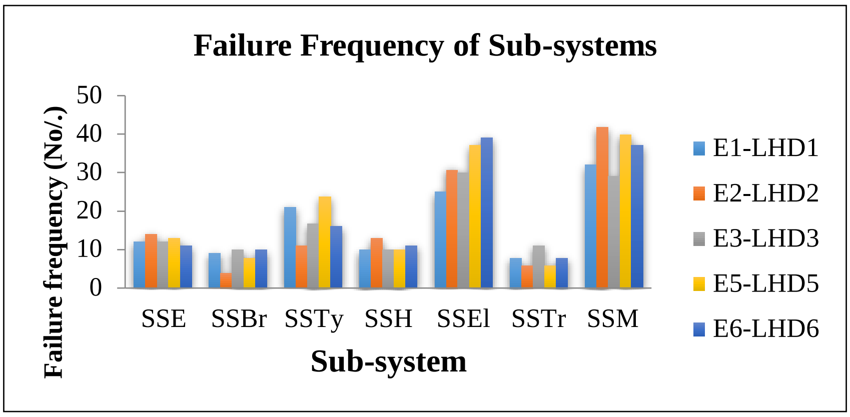


Figure 4.3 FF of sub-systems of LHDs of study area-3

Table 4.8 Percentage Availability and Utilization of LHDs of study area-2

Machine	SShr	SMhr	SAhr	BDhr	MAhr	IDhr	MWhr	% Avl.	%Utl.
LHD-1	17856	399	17458	661	16797	1519	15278	94.07	85.56
LHD-2	17856	235	17621	678	16943	1804	15139	94.89	84.78
LHD-3	17856	192	17664	24	17420	3720	13700	97.56	76.72
LHD-4	17856	178	17679	844	16835	1488	15347	94.28	85.94
LHD-5	17856	243	17613	342	17271	1386	15885	96.72	88.96

Table 4.9 Percentage Availability and Utilization of LHDs of study area-3

Machine	SShr	SMhr	SAhr	BDhr	MAhr	IDhr	MWhr	% Avl.	%Utl.
E1-LHD1	14232	542	13690	3036	10654	6271	4383	74.86	30.80
E2-LHD2	11556	354	11202	3309	7893	3847	4046	68.30	35.01
E3-LHD3	13680	570	13110	1370	11740	5859	5881	85.82	42.99
E5-LHD5	14328	597	13731	1139	12592	6201	6391	87.88	44.60
E6-LHD6	13680	570	13110	1479	11631	5341	6290	85.02	45.98

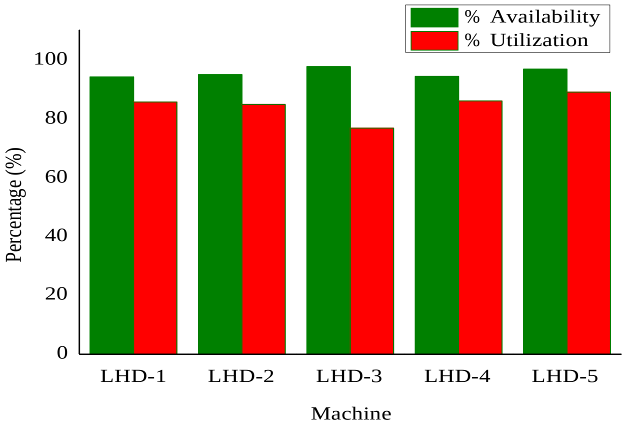


Figure 4.5 Comparison of KPIs of LHDs for study area-2

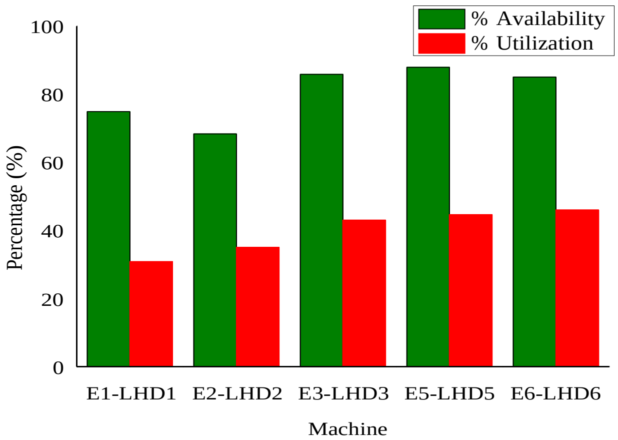


Figure 4.6 Comparison of KPIs of LHDs for study area-3

- **Trend and serial correlation test of study area-1:**

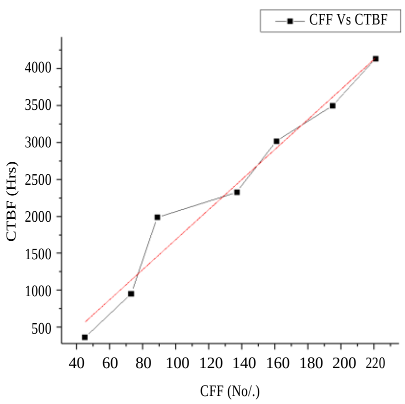


Figure 4.8 (a) Trend test of LH22

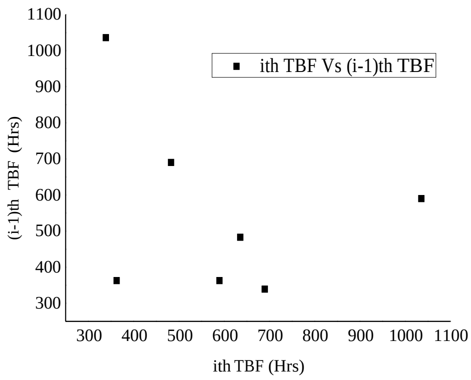


Figure 4.8 (b) Correlation test of LH22

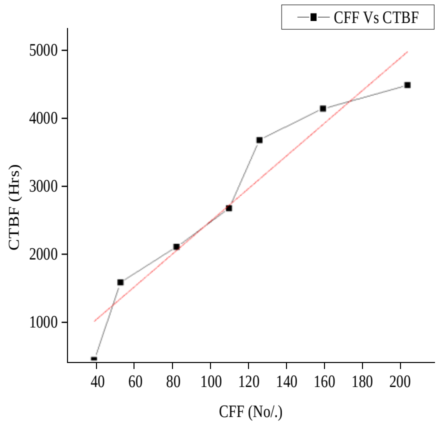


Figure 4.9 (a) Trend test of LH24

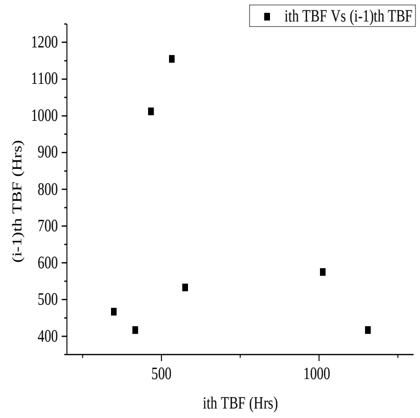


Figure 4.9 (b) Correlation test of LH24

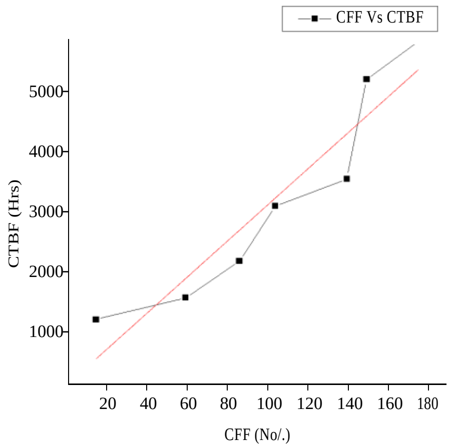


Figure 4.10 (a) Trend test of LH25

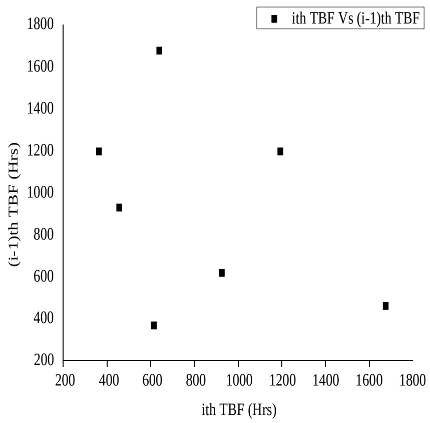


Figure 4.10 (b) Correlation test of LH25

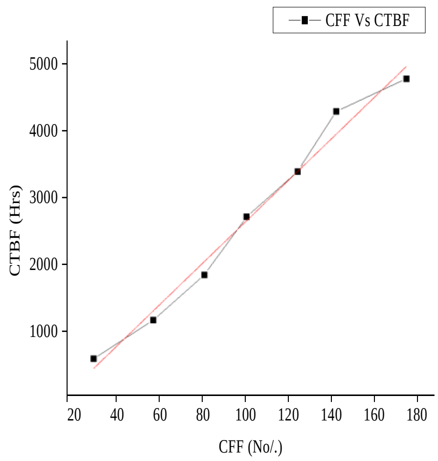


Figure 4.11 (a) Trend test of LH26

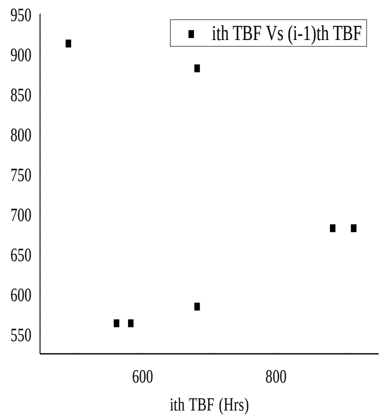


Figure 4.11 (b) Correlation test of LH26

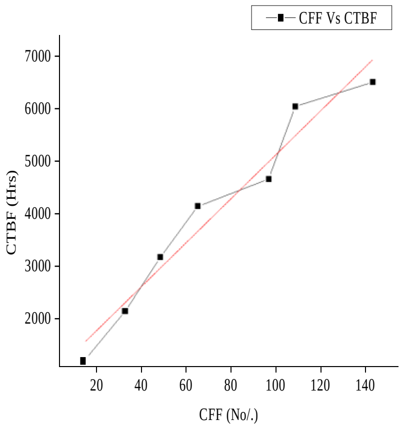


Figure 4.12 (a) Trend test of LH27

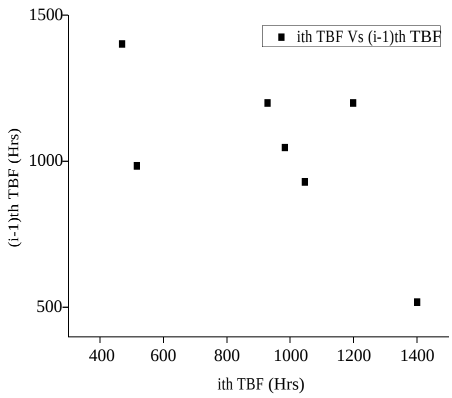


Figure 4.12 (b) Correlation test of LH27

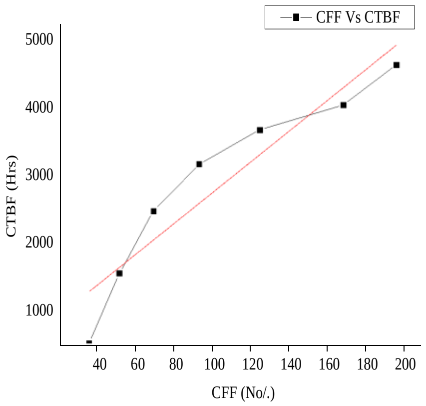


Figure 4.13 (a) Trend test of LH28

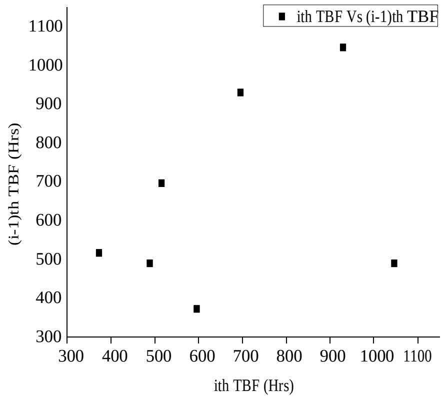


Figure 4.13 (b) Correlation test of LH28

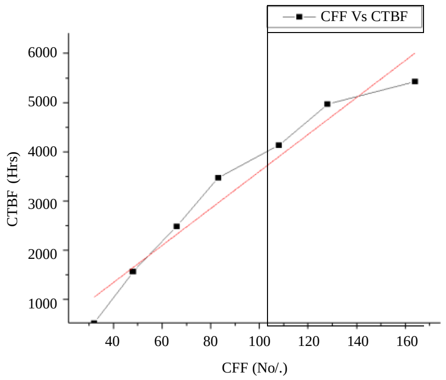


Figure 4.14 (a) Trend test of LH29

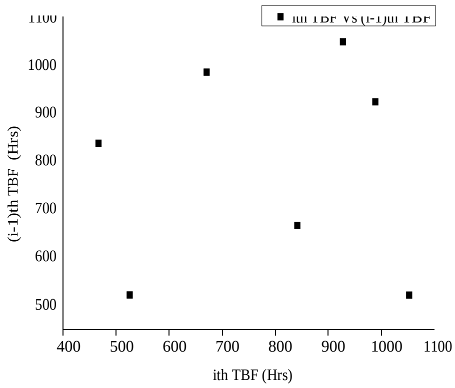
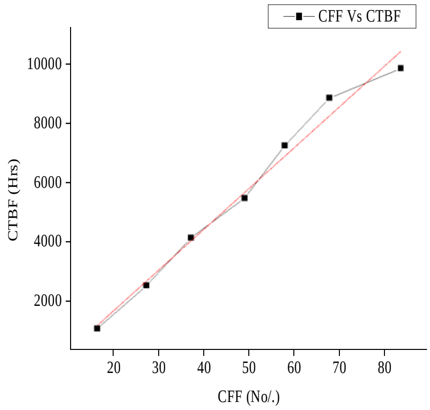


Figure 4.14 (b) Correlation test of LH29



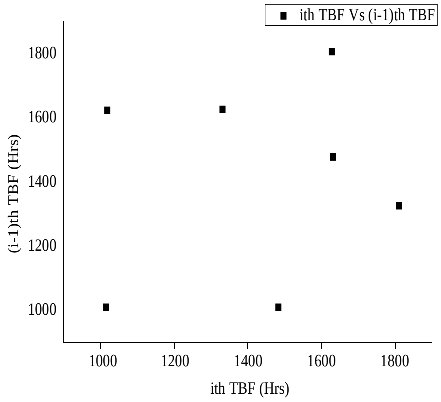
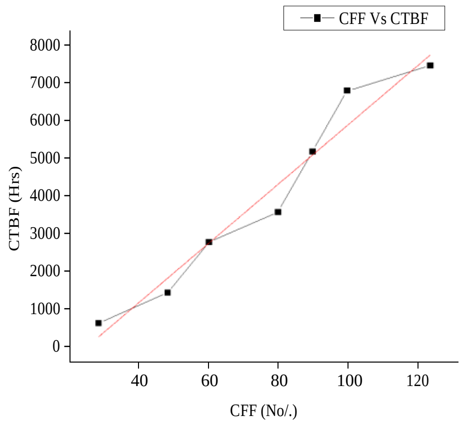


Figure 4.15 (a) Trend test of LH30 Figure 4.15 (b) Correlation test of LH30



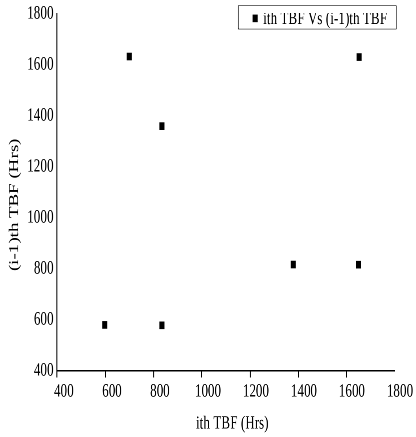
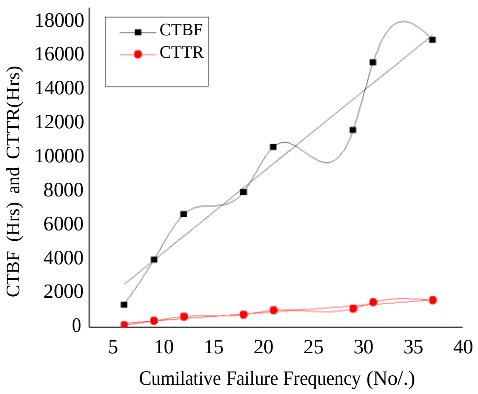


Figure 4.16 (a) Trend test of LH31 Figure 4.16 (b) Correlation test of LH31

- **Trend and serial correlation test of study area-2:**



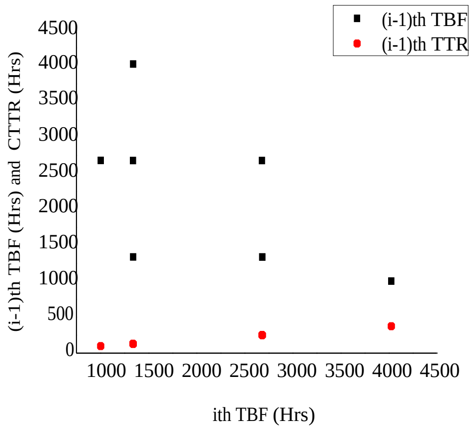


Figure 4.18 (a) Trend test for LHD-2 Figure 4.18 (b) Correlation test for LHD-2

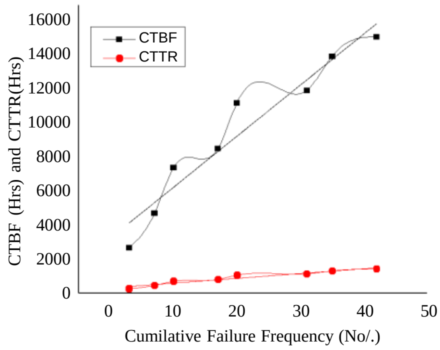


Figure 4.19 (a) Trend Test for LHD-3

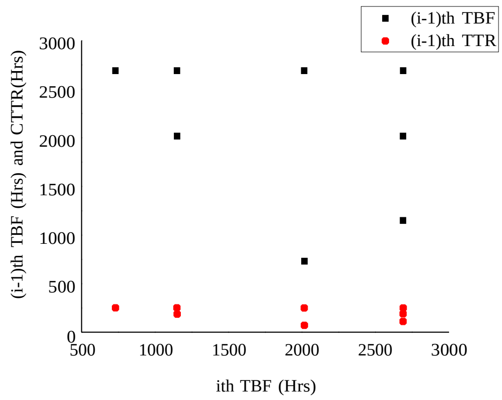


Figure 4.19 (b) Correlation Test for LHD-3

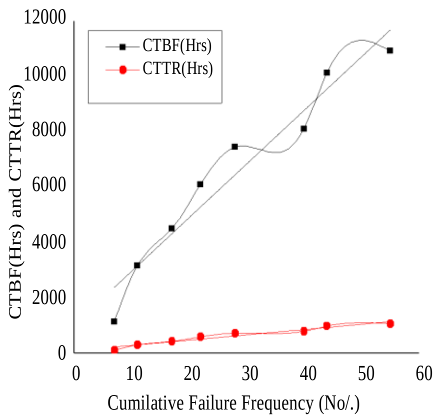


Figure 4.20 (a) Trend Test for LHD-4

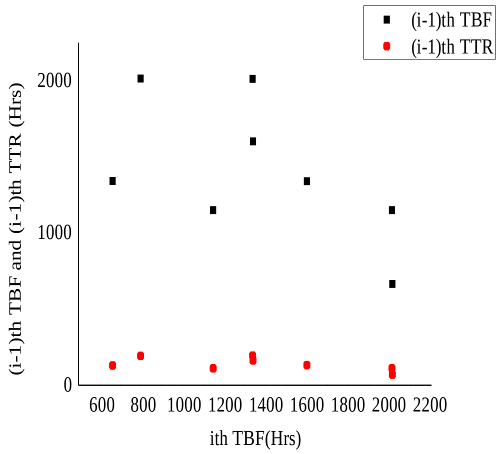


Figure 4.20 (b) Correlation Test for LHD-4

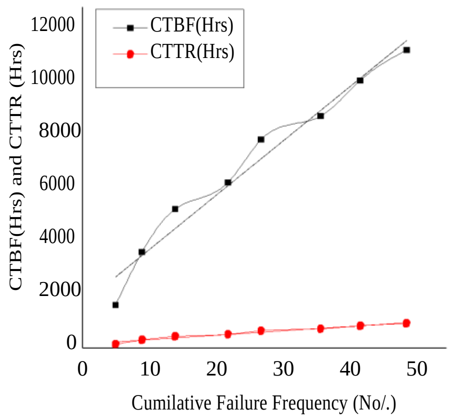


Figure 4.21 (a) Trend Test for LHD- 5

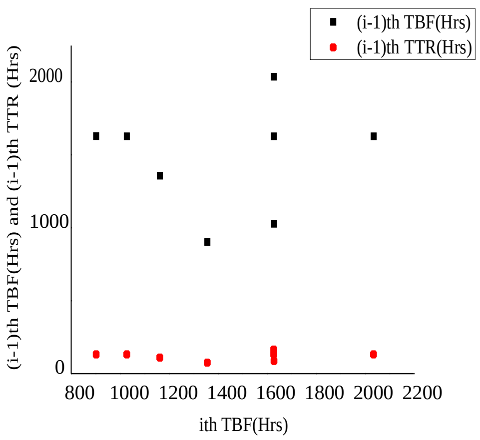
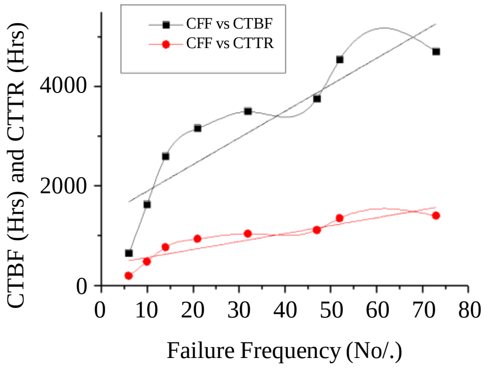


Figure 4.21 (b) Correlation Test for LHD-5

□ **Trend and serial correlation test of study area-3:**



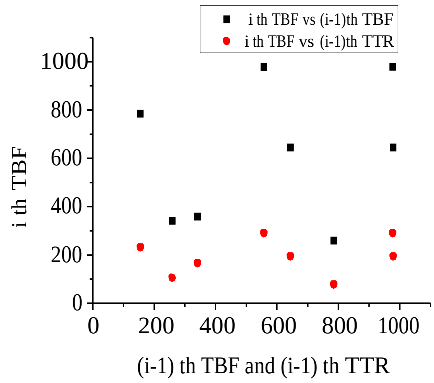
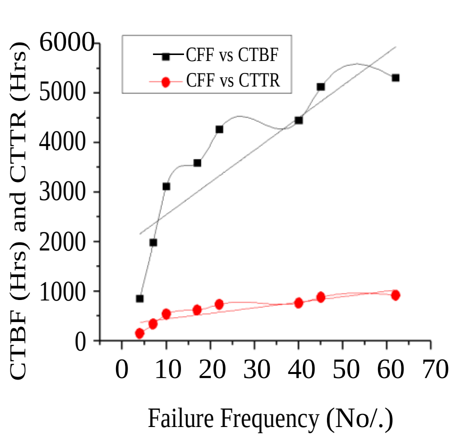


Figure 4.23 (a) Trend Test of E2-LHD2 Figure 4.23 (b) Correlation Test of E2-LHD2



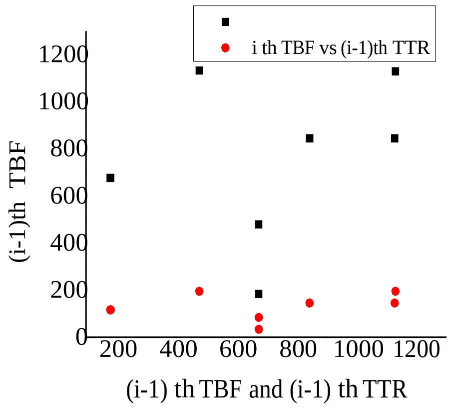
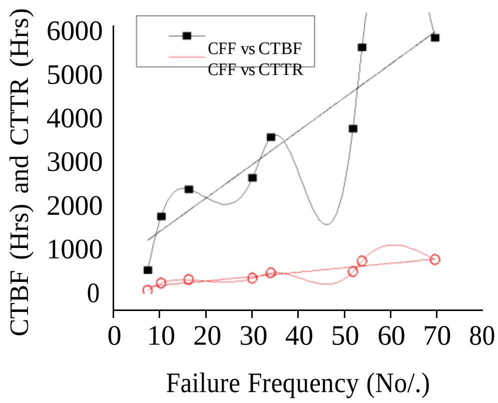


Figure 4.24 (a) Trend Test of E3-LHD3 Figure 4.24 (b) Correlation Test E3-LHD3



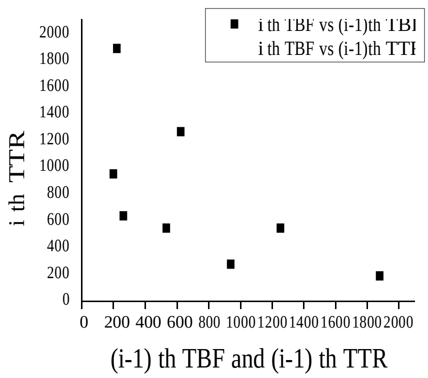
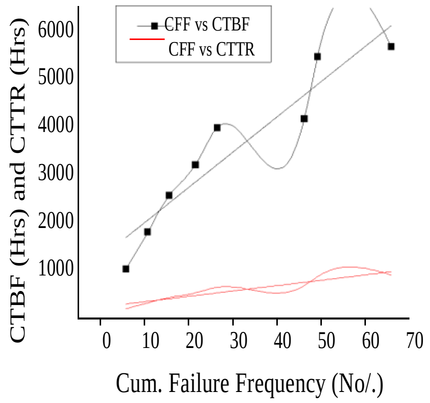


Figure 4.25 (a) Trend Test of E5-LHD Figure 4.25 (b) Correlation Test E5-LHD5



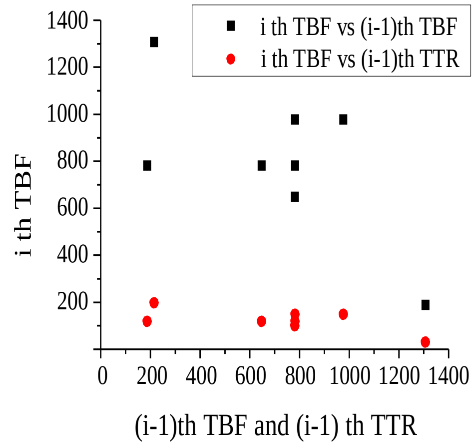


Figure 4.26 (a) Trend Test of E6-LHD6 Figure 4.26 (b) Correlation Test of E6-LHD6

Table 4.11 Results of statistic U-test for LHDs of study area-2

Machine	Data set	DOF	Calculated Statistic U	P value	Rejection of Null Hypothesis at 5% level of significance	Modelling Method
	TBF	43	14.75	1.986	14.75 <59.3 Not Rejected	RP
LHD-1	TTR	43	14.33	1.980	14.33 <59.3 Not Rejected	RP
	TBF	36	11.81	1.742	11.81 <51 Not Rejected	RP
LHD-2	TTR	36	11.85	1.722	11.58 <51 Not Rejected	RP
	TBF	41	7.15	0.791	7.15 <56.94 Not Rejected	RP
LHD-3	TTR	41	6.97	1.682	6.97 <56.94 Not Rejected	RP
	TBF	54	7.26	1.712	7.26 <72.15 Not Rejected	RP
LHD-4	TTR	54	6.84	0.689	6.84 <72.15 Not Rejected	RP
	TBF	48	6.26	0.677	6.26 <65.17 Not Rejected	RP
LHD-5	TTR	48	6.06	0.601	6.06 <65.17 Not Rejected	RP

Table 4.12 Results of statistic U-test for LHDs of study area-3

Machine	Data set	DOF	Calculated Statistic U	P value	Rejection of Null Hypothesis at 5% level of significance	Modelling Method
E1-	TBF	65	7.45	1.190	7.45 <84.82 Not Rejected	RP
LHD1	TTR	65	8.53	1.061	8.53 <84.82 Not Rejected	RP
E2-	TBF	72	10.86	1.030	10.86 <92.81 Not Rejected	RP
LHD2	TTR	72	10.32	0.810	10.32 <92.81 Not Rejected	RP
E3-	TBF	61	11.17	1.190	11.17 <80.23 Not Rejected	RP
LHD3	TTR	61	11.42	1.010	11.42 <80.23 Not Rejected	RP
E5-	TBF	75	19.56	1.894	19.56 <96.22 Not Rejected	RP
LHD5	TTR	75	19.42	1.160	19.42 <96.22 Not Rejected	RP
E6-	TBF	64	12.55	1.022	12.55 <83.68 Not Rejected	RP
LHD6	TTR	64	12.24	1.021	12.24 <83.68 Not Rejected	RP

Table 4.14 (a) Kolmogorov-Smirnov (K-S) test results of study area-2

Machine	K-S Statistics Dmax				Best Fit Model
	Exponential	Weibull 1P	Weibull 2P	Weibull 3P	
LHD-1	0.2225	0.2029	0.1593	0.0746	Weibull 3P
LHD-2	0.1439	0.1257	0.0970	0.0972	Weibull 2P
LHD-3	0.1751	0.1568	0.0946	0.0771	Weibull 3P
LHD-4	0.1491	0.1309	0.0400	0.0402	Weibull 2P
LHD-5	0.1634	0.1461	0.1057	0.1071	Weibull 2P

Table 4.14 (b) Results of MLE of study area-2

Machine	Best Fit Model	ML Estimates of the Best Fit Parameters (η=Scale/life, β=Shape, γ=Location)		
		η	Β	Γ
LHD-1	Weibull 3P	29.88	0.8365	68.3
LHD-2	Weibull 2P	191.8	1.625	0
LHD-3	Weibull 3P	446.5	0.7041	487.4
LHD-4	Weibull 2P	159.5	2.048	0
LHD-5	Weibull 2P	245.9	1.912	0

Table 4.15 (a) Kolmogorov-Smirnov (K-S) test results of study area-3

System	K-S Statistics Dmax				Best Fit Model
	Exponential	Weibull 1P	Weibull 2P	Weibull 3P	
E1-LHD1	0.1462	0.1298	0.1087	0.1098	Weibull 2P
E2-LHD2	0.1278	0.1092	0.0471	0.0468	Weibull 3P
E3-LHD3	0.1244	0.1029	0.0651	0.0519	Weibull 3P
E5-LHD5	0.0686	0.0635	0.0535	0.0458	Weibull 3P
E6-LHD6	0.1497	0.1283	0.0974	0.0800	Weibull 3P

Table 4.15 (b) Results of MLE of study area-3

System	Best Fit Model	ML Estimates of the Best Fit Parameters (η=Scale/life, β=Shape, γ=Location)		
		η	Β	Γ
E1-LHD1	Weibull 2P	162.9	1.541	0
E2-LHD2	Weibull 3P	208.3	1.802	-4.245
E3-LHD3	Weibull 3P	233.3	3.264	-93.92
E5-LHD5	Weibull 3P	70.48	0.668	24.75
E6-LHD6	Weibull 3P	570.9	10.16	-437.4

- **Plots of FR and PDF of study area-1:**

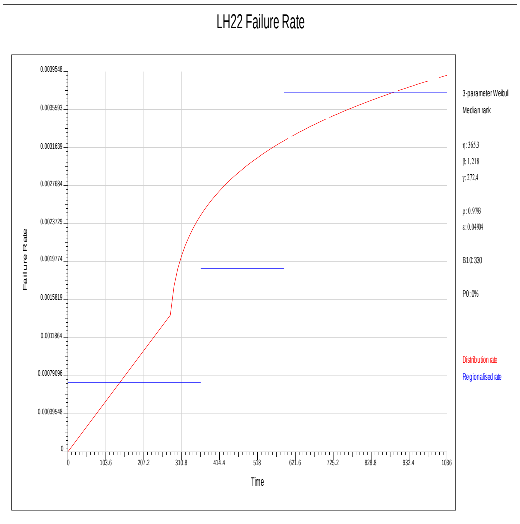


Figure 4.28 (a) FR of LH22

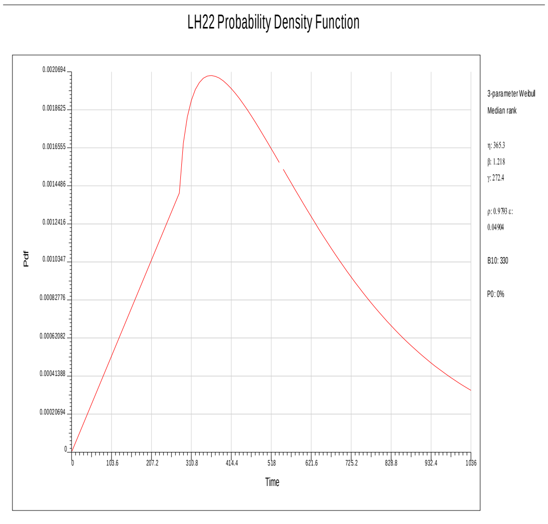


Figure 4.28 (b) PDF of LH22

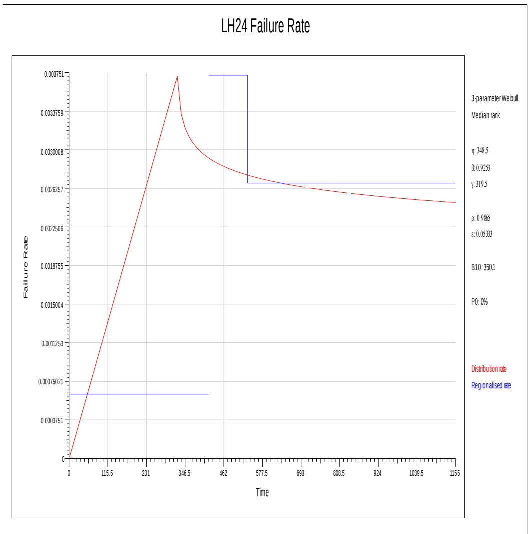


Figure 4.29 (a) FR of LH24

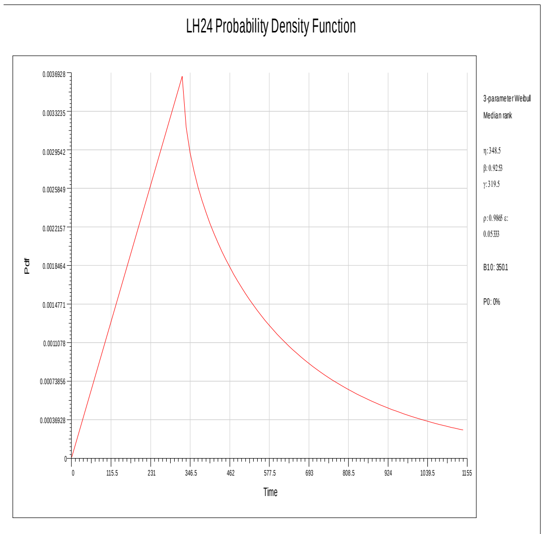
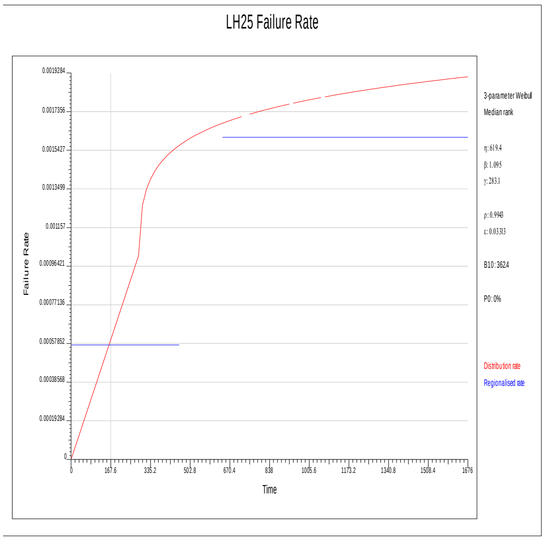


Figure 4.29 (b) PDF of LH24



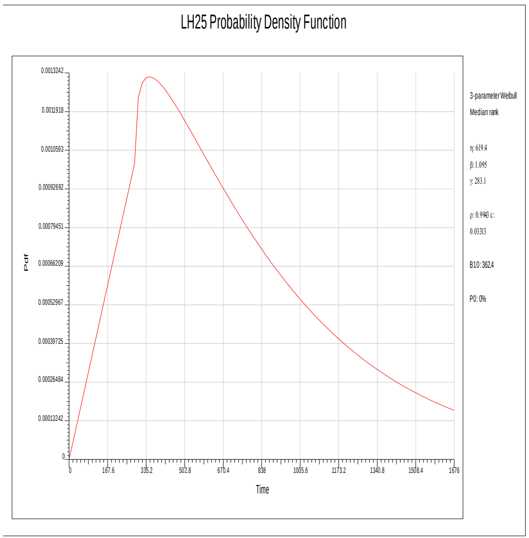
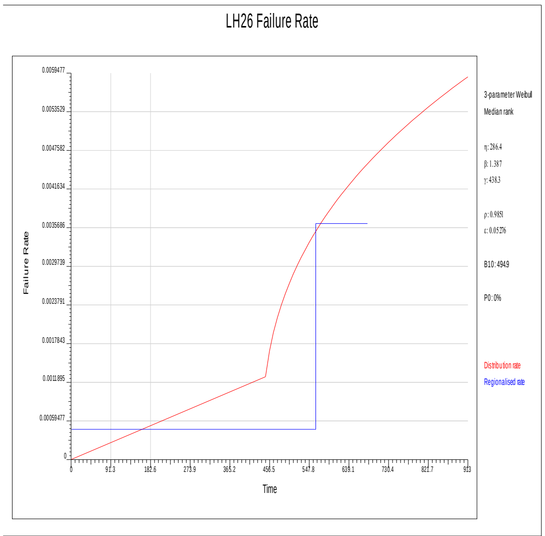


Figure 4.30 (a) FR of LH25 Figure 4.30 (b) PDF of LH25



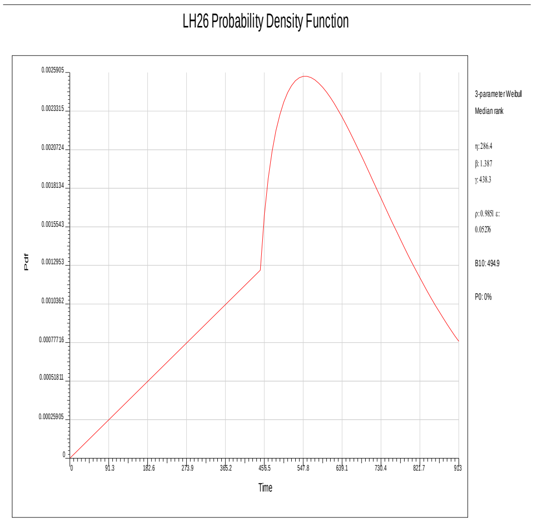
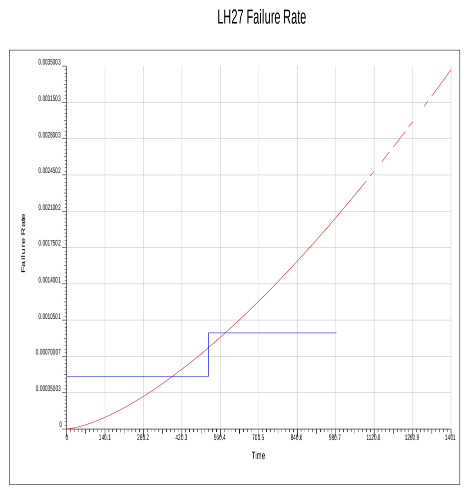


Figure 4.31 (a) FR of LH26 Figure 4.31 (b) PDF of LH26



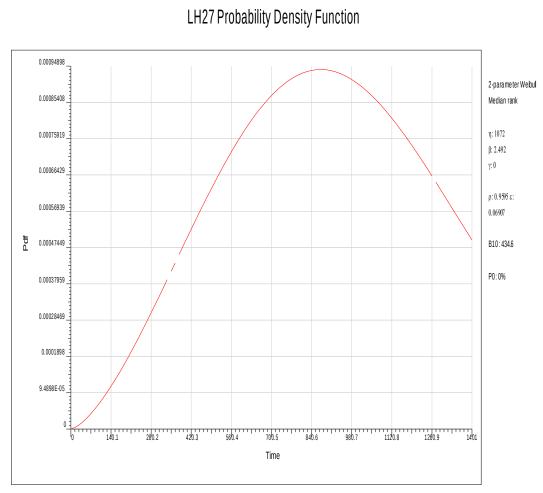


Figure 4.32 (a) FR of LH27 Figure 4.32 (b) PDF of LH27

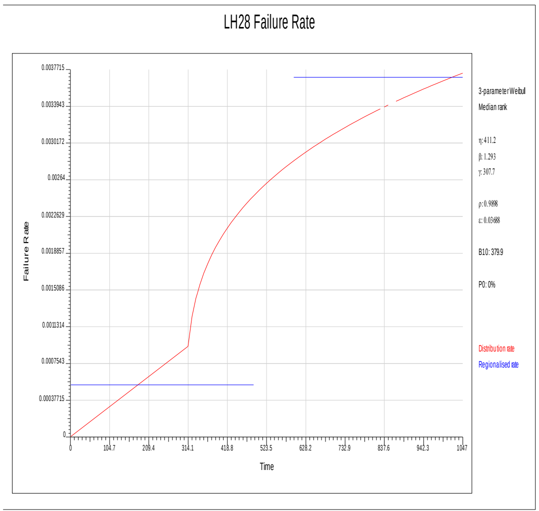


Figure 4.33 (a) FR of LH28

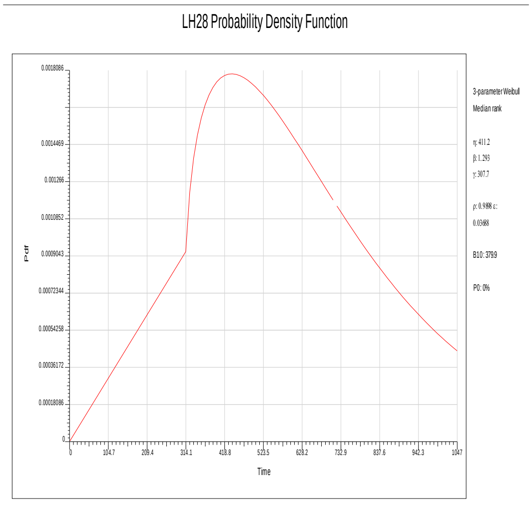


Figure 4.33 (b) PDF of LH28

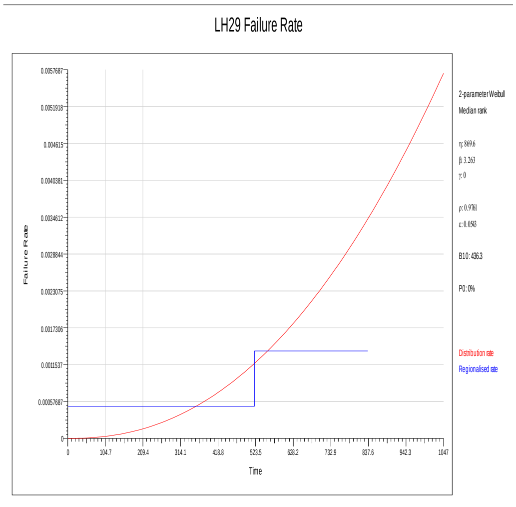


Figure 4.34 (a) FR of LH29

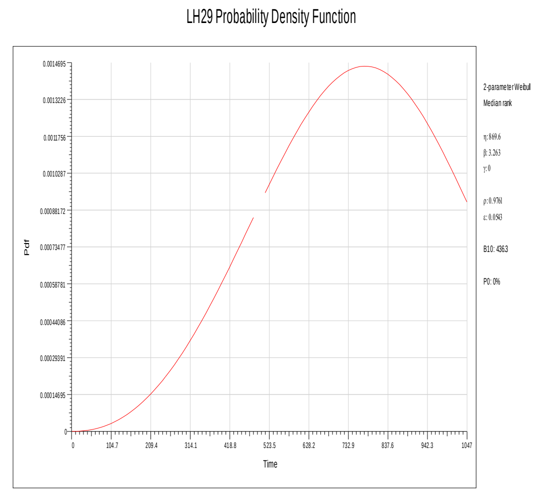


Figure 4.34 (b) PDF of LH29

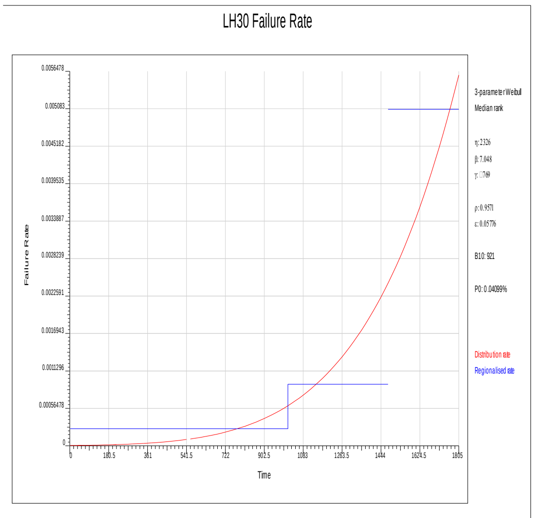


Figure 4.35 (a) FR of LH30

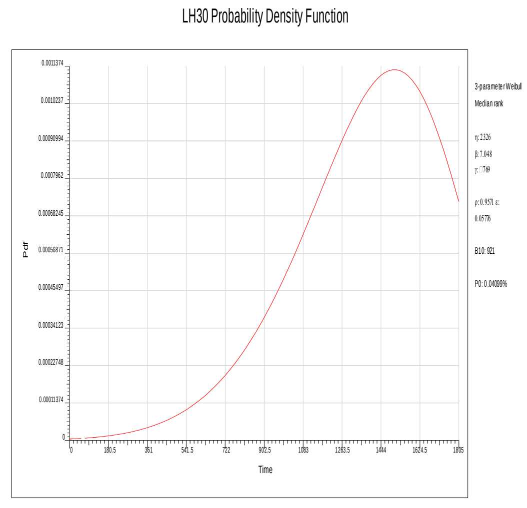


Figure 4.35 (b) PDF of LH30

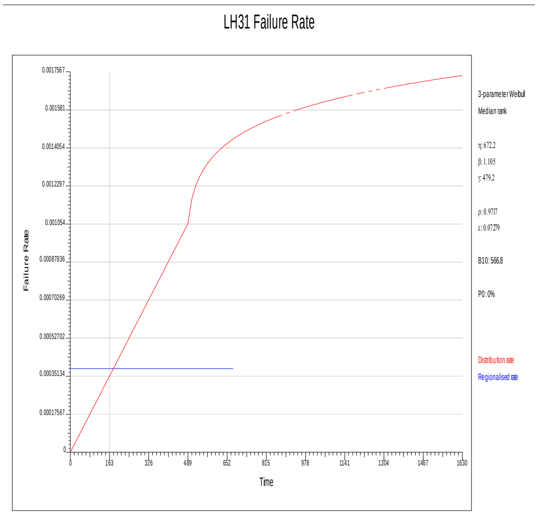


Figure 4.36 (a) FR of LH31

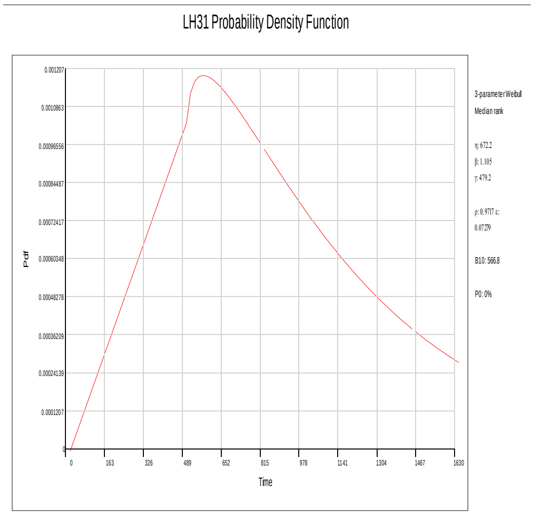


Figure 4.36 (b) PDF of LH31

Table 4.17 Results of FR and PDF of LHDs of study area-2

Machine	**Parameter**	**SSE**	**SSBr**	**SSTy**	**SSH**	**SSEl**	**SSTr**	**SSM**
LHD-1	TBF	1615	2021	897	1614	1153	4046	1008
	FR	0.0140	0.0244	0.0328	0.0278	0.0256	0.0233	0.0226
	PDF	0.0130	0.025	0.0210	0.0098	0.0053	0.0030	0.0011
LHD-2	TBF	1340	2683	1338	2684	1003	4026	1340
	FR	0.0024	0.0038	0.0058	0.0067	0.0075	0.0083	0.0090
	PDF	0.0023	0.0033	0.0039	0.0038	0.0035	0.0031	0.0027
LHD-3	TBF	2691	2017	1150	2690	731	2018	1151
	FR	0.0018	0.0036	0.0023	0.0018	0.0016	0.0014	0.0013
	PDF	0.0017	0.0034	0.0016	0.0009	0.0006	0.0004	0.0002
LHD-4	TBF	1150	2012	1602	1342	665	2014	800
	FR	0.0018	0.0039	0.0080	0.0102	0.0123	0.0145	0.0166
	PDF	0.0018	0.0035	0.0053	0.0053	0.0048	0.0040	0.0031
LHD-5	TBF	1627	2035	1027	1628	902	1356	1162
	FR	0.0013	0.0026	0.0049	0.0060	0.0071	0.0082	0.0093
	PDF	0.0013	0.0023	0.0033	0.0030	0.0026	0.0021	0.0016

- **Plots of FR and PDF of study area-2:**

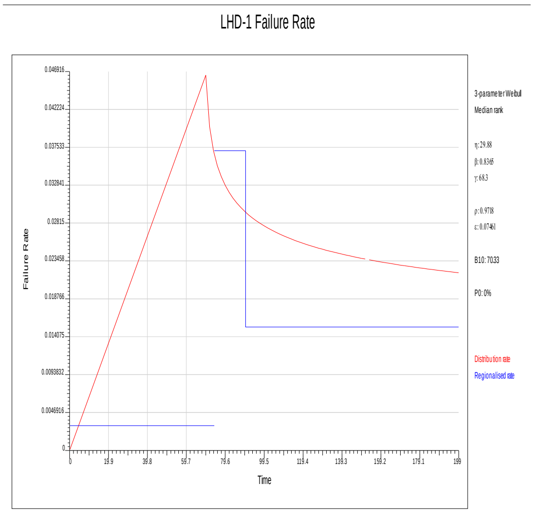


Figure 4.37 (a) FR of LHD-1

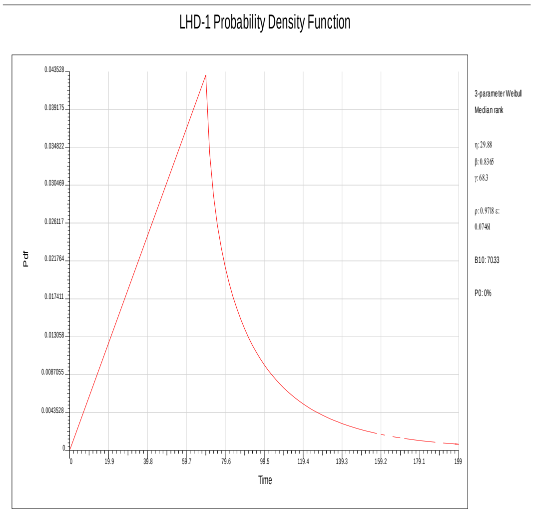


Figure 4.37 (b) PDF of LHD-1

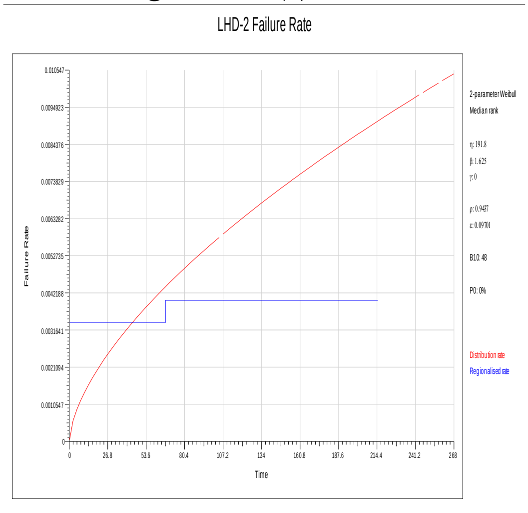


Figure 4.38 (a) FR of LHD-2

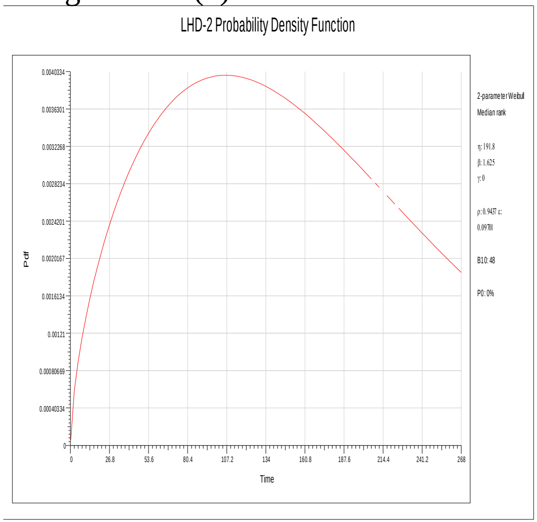


Figure 4.38 (b) PDF of LHD-2

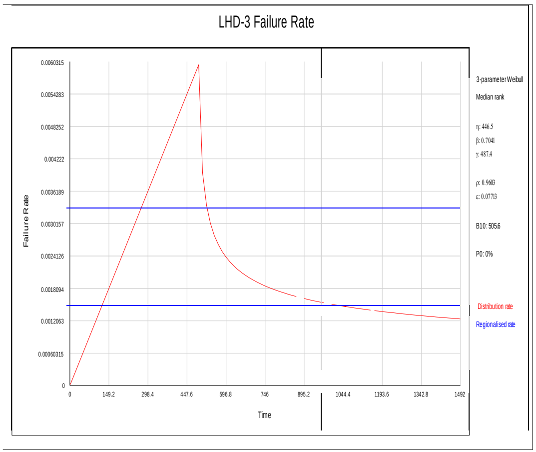


Figure 4.39 (a) FR of LHD-3

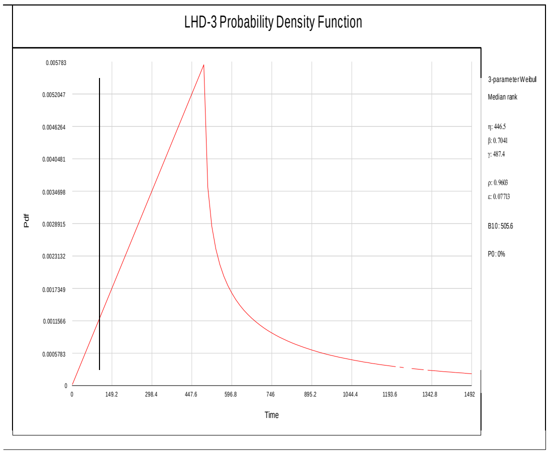
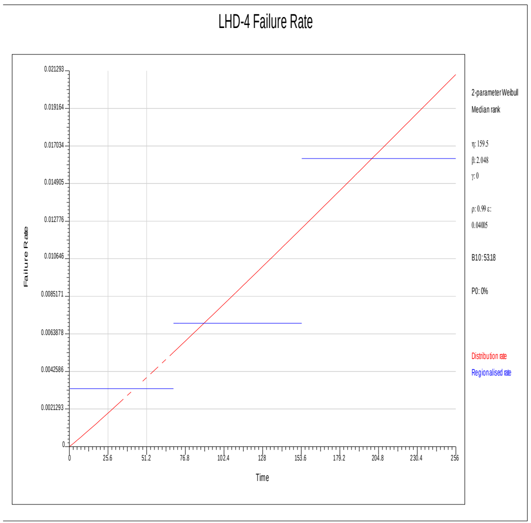


Figure 4.39 (b) PDF of LHD-3



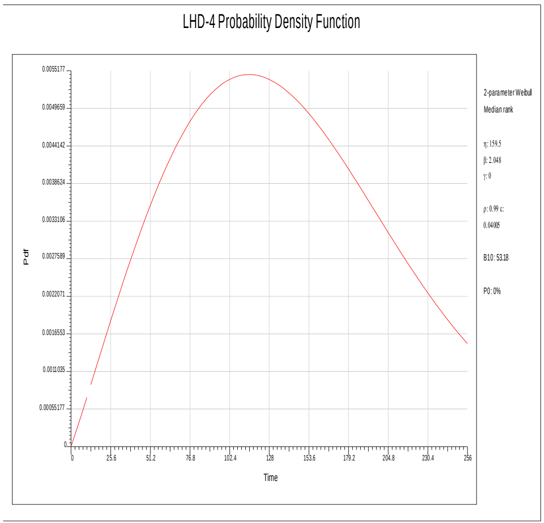
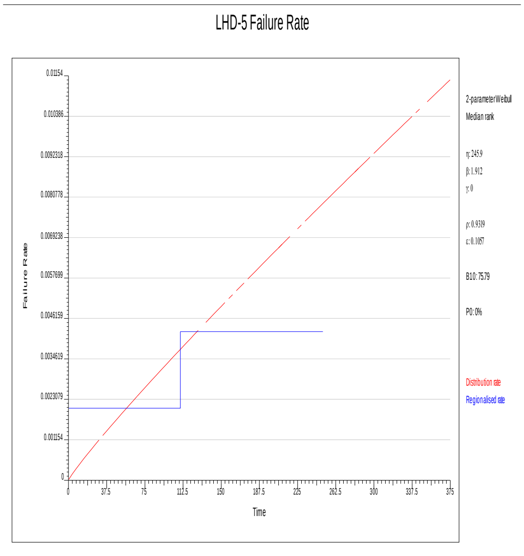


Figure 4.40 (a) FR of LHD-4 Figure 4.40 (b) PDF of LHD-4



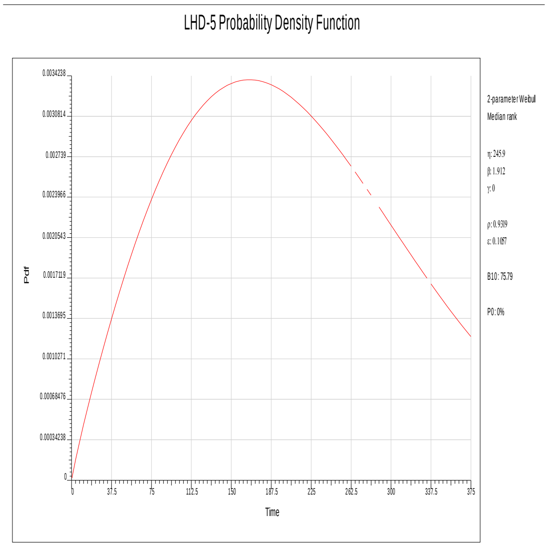
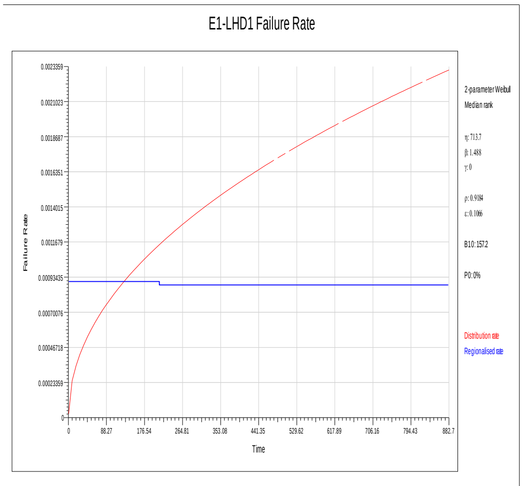


Figure 4.41 (a) FR of LHD-5 Figure 4.41 (b) PDF of LHD-5

Table 4.18 Results of FR and PDF of LHDs of study area-3

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
E1-LHD1	TBF	881	883	288	883	211	880	2012
	FR	0.0027	0.0027	0.0046	0.0027	0.0044	0.0027	0.0044
	PDF	0.0106	0.0106	0.0063	0.0106	0.0053	0.0106	0.0053
E2-LHD2	TBF	644	979	558	341	259	785	155
	FR	0.0085	0.0104	0.0076	0.0055	0.0044	0.0095	0.0032
	PDF	0.0032	0.0022	0.0035	0.0038	0.0035	0.0027	0.0029
E3-LHD3	TBF	845	1129	478	676	183	676	181
	FR	0.0135	0.0225	0.0088	0.0110	0.0039	0.0110	0.0039
	PDF	0.0054	0.0030	0.0052	0.0054	0.0039	0.0054	0.0033
E5-LHD5	TBF	535	1254	264	940	202	1879	222
	FR	0.0106	0.0074	000134	0.0084	0.0765	0.0064	0.0134
	PDF	0.0048	0.0014	0.0081	0.0024	0.0754	0.0007	0.0081
E6-LHD6	TBF	977	782	648	781	188	1307	215
	FR	0.0259	0.0138	0.0099	0.0138	0.0023	0.0467	0.0034
	PDF	0.0056	0.0064	0.0058	0.0064	0.0020	0.0025	0.0029

- **Plots of FR, and PDF of study area 3:**



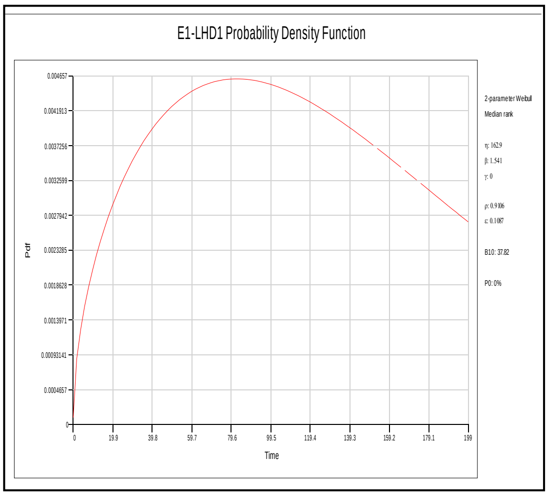
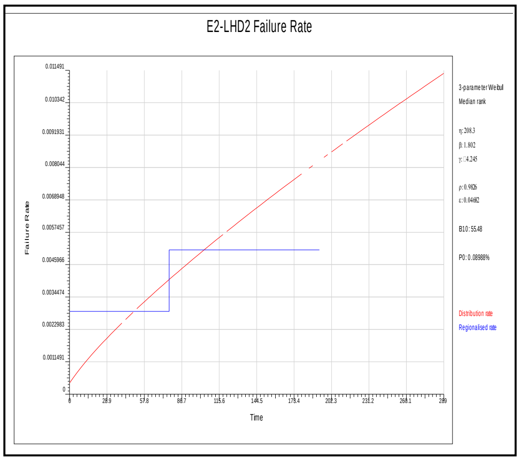


Figure 4.42 (a) FR of E1-LHD1 Figure 4.42 (b) PDF of E1-LHD1



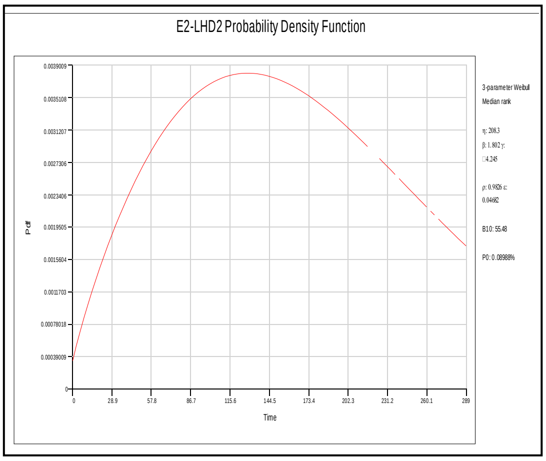
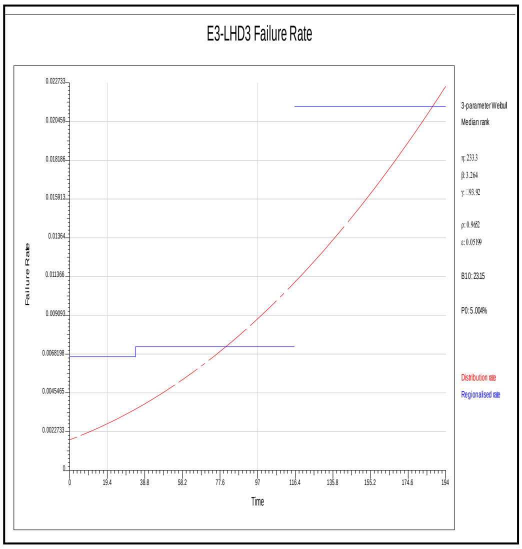


Figure 4.43 (a) FR of E2-LHD2 Figure 4.43 (b) PDF of E2-LHD2



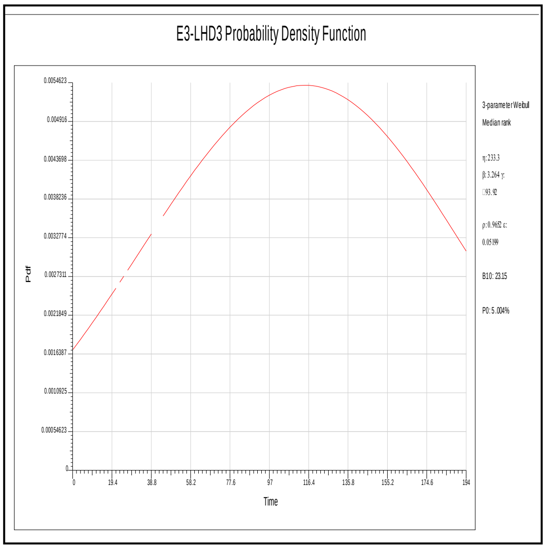
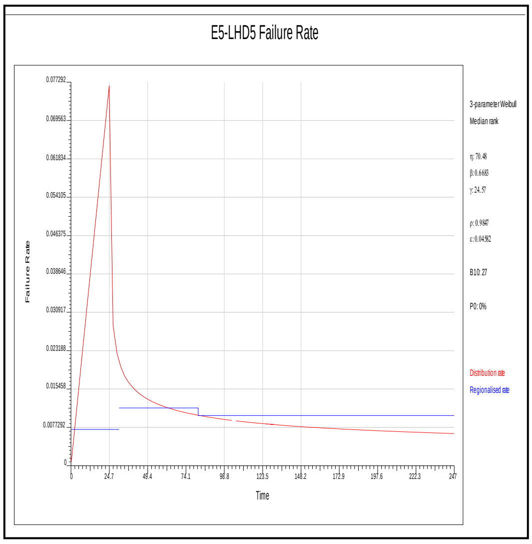


Figure 4.44 (a) FR of E3-LHD3 Figure 4.44 (b) PDF of E3-LHD3



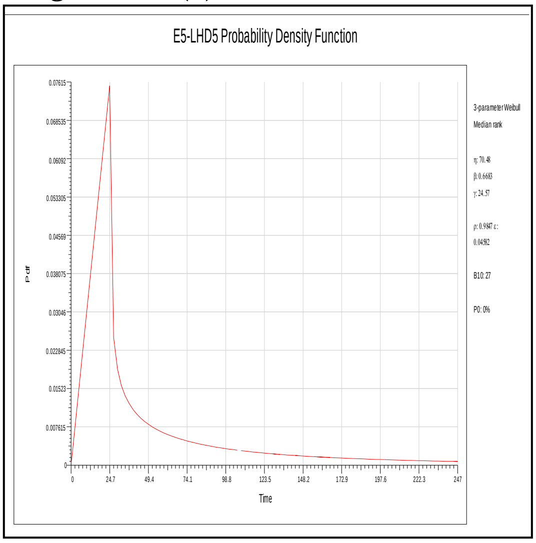
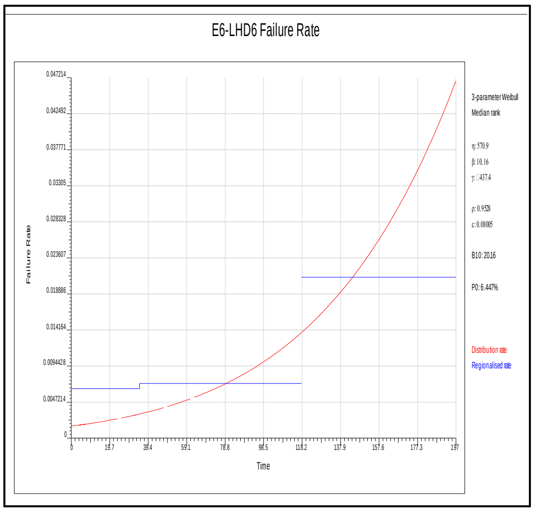


Figure 4.45 (a) FR of E5-LHD5 Figure 4.45 (b) PDF of E5-LHD5



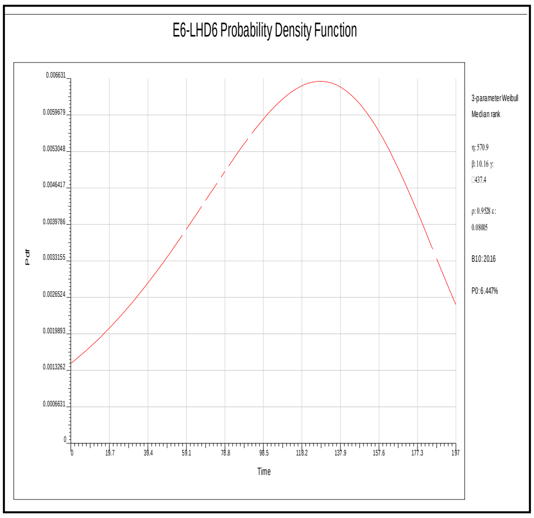


Figure 4.46 (a) FR of E6-LHD6 Figure 4.46 (b) PDF of E6-LHD6

Table 4.20 Percentage of reliability and unreliability of study area-2

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
LHD-1 (3P W)	TBF	1615	2021	897	1614	1153	4046	1008
	F%	46.27	65.08	20.56	50.58	67.32	36.24	46.23
	R%	53.73	34.92	79.44	49.42	32.68	63.76	53.77
LHD-2 (2P W)	TBF	1340	2683	1338	2684	1003	4026	1340
	F%	36.78	61.96	51.34	31.52	42.66	55.39	17.25
	R%	63.22	38.04	48.66	68.48	57.34	44.61	82.75
LHD-3 (3P W)	TBF	2691	2017	1150	2690	731	2018	1151
	F%	29.78	52.84	37.01	32.78	54.36	49.88	18.39
	R%	70.22	47.16	62.99	67.22	45.64	50.12	81.62
LHD-4 (2P W)	TBF	1150	2012	1602	1342	665	2014	800
	F%	38.10	50.22	39.69	34.45	53.94	51.49	20.12
	R%	61.90	49.78	60.31	65.55	46.06	48.51	79.88
LHD-5 (2P W)	TBF	1627	2035	1027	1628	902	1356	1162
	F%	31.45	33.76	38.52	33.62	53.12	59.34	39.39
	R%	68.55	66.24	61.48	66.38	46.88	40.66	60.61

Table 4.21 Percentage of reliability and unreliability of study area-3

Machine	Parameter	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
E1-LHD1	F (%)	30.78	61.66	59.01	27.78	18.33	48.88	44.36
	R (%)	69.22	38.34	40.99	72.22	81.67	51.12	55.64
	TBF (hours)	881	883	288	883	211	880	2012
E2-LHD2	F (%)	24.78	77.66	50.36	29.78	19.33	48.88	50.01
	R (%)	75.22	22.34	49.64	70.22	80.67	51.12	49.99
	TBF (hours)	644	979	558	341	259	785	155
E3-LHD3	F (%)	30.78	61.66	59.01	27.78	18.33	48.88	44.36
	R (%)	69.22	38.34	40.99	72.22	81.67	51.12	55.64
	TBF (hours)	845	1129	478	676	183	676	181
E5-LHD5	F (%)	29.78	50.01	77.66	24.36	20.33	48.88	51.33
	R (%)	70.22	49.99	22.34	75.64	79.67	51.12	48.67
	TBF (hours)	535	1254	264	940	202	1879	222
E6-LHD6	F (%)	48.88	62.66	59.01	27.78	18.33	30.78	49.84
	R (%)	51.12	37.34	40.99	72.22	81.67	69.22	50.16
	TBF (hours)	977	782	648	781	188	1307	215

Table 4.23 Results of percentage availability and maintainability of study area-2

Machine	Total number of failures	MTBF (hours)	MTTR (hours)	Availability (%)	Maintainability (%)
LHD-1	74	101.47	10.7	91.53	98.26
LHD-2	81	112.7	16.07	92.39	99.98
LHD-3	31	459.45	234.5	97.7	99.00
LHD-4	60	190.56	18.51	85.9	96.48
LHD-5	37	485.81	45.54	97.12	99.00

Table 4.24 Results of percentage availability and maintainability of study area-3

Machine	Total number of failures	MTBF (hours)	MTTR (hours)	Availability (%)	Maintainability (%)
E1-LHD1	66	72.68	16.59	84.94	99.89
E2-LHD2	73	64.35	19.24	69.48	99.01
E3-LHD3	62	85.48	14.74	87.45	98.65
E5-LHD5	70	84.58	11.12	88.82	97.12
E6-LHD6	65	87.38	13.27	87.42	98.60

Table 4.26 Preventive Maintenance time intervals of study area-2

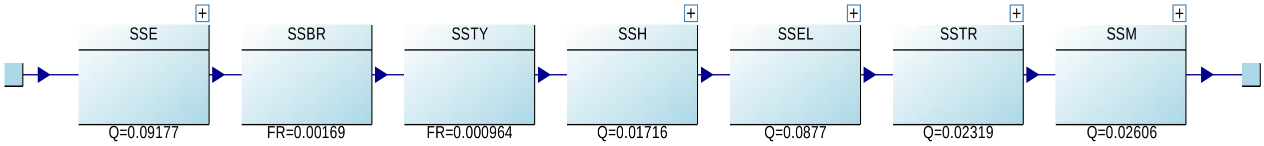
Reliability Level	**Maintenance Interval, (hours)**				
	LHD-1	**LHD-2**	**LHD-3**	**LHD-4**	**LHD-5**
Distribution	**3 P W**	**2 P W**	**3 P W**	**2 P W**	**2 P W**
Parameters	η= 29.88 β=0.8365 γ= 68.3	η= 191.8 β= 1.625 γ= 0	η= 446.5 β=0.7041 γ= 487.4	η= 159.5 β= 2.048 γ= 0	η= 245.9 β= 1.912 γ= 0
0.90	70	48	506	53	76
0.80	73	76	540	77	112
0.70	77	102	591	96	143

Table 4.27 Preventive Maintenance time intervals of study area-3

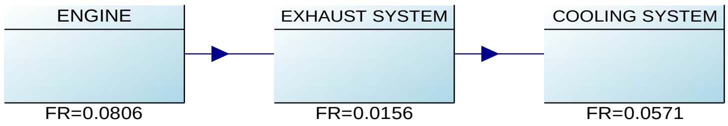
Reliability Level	**Preventive Maintenance Time Interval, (hours)**				
	E1-LHD1	**E2-LHD2**	**E3-LHD3**	**E5-LHD5**	**E6-LHD6**
Distribution	**2P W**	**3 P W**	**3 P W**	**3 P W**	**3 P W**
Parameters	η= 162.9 β= 1.541 γ= 0	η= 208.3 β= 1.802 γ= -4.245	η= 233.3 β= 3.264 γ= -93.92	η= 70.48 β= 0.668 γ= 24.75	η= 570.9 β= 10.16 γ= -437.4
0.90	38	56	23	27	20
0.80	62	87	54	32	55
0.70	84	114	76	40	79

APPENDIX-2

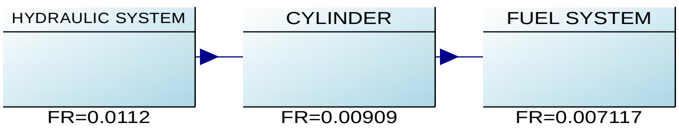
- **Series configured RBDs for study area-1:**



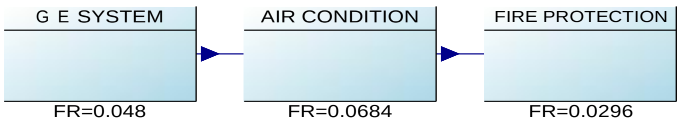
Engine Subsystem:



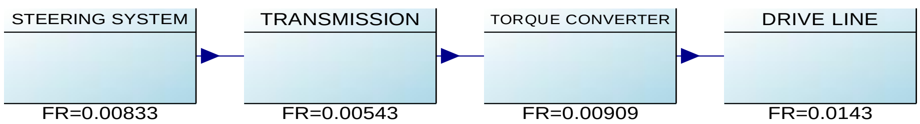
Hydraulic Subsystem:



Electrical Subsystem:



Transmission Subsystem:



Mechanical Subsystem:

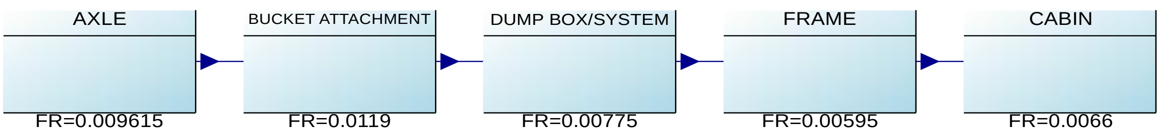


Figure 5.2 Reliability Block Diagram (RBD) of LH22

Developed mathematical models of RBD for LHDs in study area-1:

$$_{22}(\ ) = -(\frac{363-272.4}{365.4})^{1.218} \times -(\frac{590-272.4}{365.4})^{1.218} \times -(\frac{1036-272.4}{365.4})^{1.218} \times -(\frac{339-272.4}{365.4})^{1.218}$$
$$\times -(\frac{690-272.4}{365.4})^{1.218} \times -(\frac{483-272.4}{365.4})^{1.218}$$
$$\times -(\frac{636-272.4}{365.4})^{1.218} \qquad (5.7)$$

$$_{22}(\ ) = 0.8328 \times 0.4302 \times 0.2856 \times 0.8808 \times 0.3074 \times 0.5982 \times 0.3694 \qquad (5.8)$$

$$y \qquad y_{\ i=1} \quad \times 100$$

$$(\ _{22}) = \prod^{n}$$

$$= 66.48\% \qquad (5.9)$$

$$_{24}(\ ) = -(\frac{417-319.5}{348.5})^{0.9253} \times -(\frac{1158-319.5}{348.5})^{0.9253} \times -(\frac{533-319.5}{348.5})^{0.9253} \times -(\frac{575-319.5}{348.5})^{0.9253}$$
$$\times -(\frac{1012-319.5}{348.5})^{0.9253} \times -(\frac{467-319.5}{348.5})^{0.9253}$$
$$\times -(\frac{349-319.5}{348.5})^{0.9253} \qquad (5.10)$$

$$_{24}(\ ) = 0.7334 \times 0.2056 \times 0.5292 \times 0.4722 \times 0.3514 \times 0.6360 \times 0.9032 \qquad (5.11)$$

$$y \qquad y_{\ i=1} \quad \times 100$$

$$(\ _{24}) = \prod^{n}$$

$$= 56.77\% \qquad (5.12)$$

$$_{25}(\ ) = -(\frac{1194-283.1}{619.4})^{1.095} \times -(\frac{364-283.1}{619.4})^{1.095} \times -(\frac{615-283.1}{619.4})^{1.095} \times -(\frac{926-283.1}{619.4})^{1.095}$$
$$\times -(\frac{457-283.1}{619.4})^{1.095} \times -(\frac{1676-283.1}{619.4})^{1.095}$$
$$\times -(\frac{640-283.1}{619.4})^{1.095} \qquad (5.13)$$

$$_{25}(\ ) = 0.2173 \times 0.8978 \times 0.6031 \times 0.3525 \times 0.7786 \times 0.2881 \times 0.5780 \qquad (5.14)$$

$$y \qquad y_{\ i=1} \quad \times 100$$

$$(\ _{25}) = \prod^{n}$$

$$= 60.03\% \qquad (5.15)$$

$$_{26}(\ ) = {}^{-(}\frac{563-438.3}{286.4})^{01.387} \times {}^{-(}\frac{584-438.3}{286.4})^{01.387} \times {}^{-(}\frac{682-438.3}{286.4})^{01.387} \times {}^{-(}\frac{882-438.3}{286.4})^{01.387}$$

$$\times {}^{-(}\frac{682-438.3}{286.4})^{01.387} \times {}^{-(}\frac{913-438.3}{286.4})^{01.387}$$

$$\times {}^{-(}\frac{492-438.3}{286.4})^{01.387} \qquad (5.16)$$

$$_{26}(\ ) = 0.7275 \times 0.6749 \times 0.4479 \times 0.2095 \times 0.4481 \times 0.2026 \times 0.9061 \qquad (5.17)$$

y $\qquad$ y $_{i=1}$ $\times 100$

$(\ _{26}) = \prod^{n}$

$= 59.98\%$ (5.18)

$_{27}(\ ) = -(\frac{1199-0}{1072})^{2.492} \times -(\frac{929-0}{1072})^{2.492} \times -(\frac{1047-0}{1072})^{2.492} \times -(\frac{984-0}{1072})^{2.492}$
$\times -(\frac{517-0}{1072})^{2.492} \times -(\frac{1401-0}{1072})^{2.492}$
$\times -(\frac{470-0}{1072})^{2.492}$ (5.19)

$_{27}(\ ) = 0.2666 \times 0.4961 \times 0.3892 \times 0.4452 \times 0.8499 \times 0.2423$
$\times 0.8793$ (5.20)

y $\qquad$ y $_{i=1}$ $\times 100$

$(\ _{27}) = \prod^{n}$

$= 68.65\%$ (5.21)

$_{28}(\ ) = -(\frac{489-307.1}{411.2})^{1.293} \times -(\frac{489-307.1}{411.2})^{1.293} \times -(\frac{489-307.1}{411.2})^{1.293} \times -(\frac{489-307.1}{411.2})^{1.293}$
$\times -(\frac{489-307.1}{411.2})^{1.293} \times -(\frac{489-307.1}{411.2})^{1.293}$
$\times -(\frac{489-307.1}{411.2})^{1.293}$ (5.22)

$_{28}(\ ) = 0.7051 \times 0.2178 \times 0.2806 \times 0.3935 \times 0.6584 \times 0.9096$
$\times 0.5302$ (5.23)

y $\qquad$ y $_{i=1}$ $\times 100$

$(\ _{28}) = \prod^{n}$

$= 65.63\%$ (5.24)

$_{29}(\ ) = -(\frac{520-0}{869.6})^{3.263} \times -(\frac{1047-0}{869.6})^{3.263} \times -(\frac{922-0}{869.6})^{3.263} \times -(\frac{983-0}{869.6})^{3.263}$
$\times -(\frac{665-0}{869.6})^{3.263} \times -(\frac{836-0}{869.6})^{3.263}$
$\times -(\frac{461-0}{869.6})^{3.263}$ (5.25)

$_{29}(\ ) = 0.8288 \times 0.2599 \times 0.3970 \times 0.3244 \times 0.6590 \times 0.4142$
$\times 0.8811$ (5.26)

y $\qquad$ y $_{i=1}$ $\times 100$

$(\ _{29}) = \prod^{n}$

$= 69.44\%$ (5.27)

$_{30}(\ ) = (\frac{1009+769}{2326})^{7.048} \times (\frac{1477+769}{2326})^{7.048} \times (\frac{1625+769}{2326})^{7.048} \times (\frac{1352+769}{2326})^{7.048}$

$$_{2326}\;)$$

$$\times \quad ^{-\left(\frac{1805+769}{2326}\right)^{7.048}} \times \quad ^{-\left(\frac{1622+769}{2326}\right)^{7.048}}$$

$$\times \quad ^{-\left(\frac{1012+769}{2326}\right)^{7.048}} \tag{5.28}$$

$$_{30}(\quad) = 0.8599 \times 0.4575 \times 0.3929 \times 0.5928 \times 0.2293 \times 0.3963 \times 0.8586 \tag{5.29}$$

$$y \qquad y_{i=1} \times 100$$

$$(\ _{30}) = \prod^{n}$$

$$= 69.41\% \tag{5.30}$$

$$_{31}(\ ) = {}^{-(}\frac{576-479.2}{672.2})^{1.105} \times {}^{-(}\frac{813-479.2}{672.2})^{1.105} \times {}^{-(}\frac{1357-479.2}{672.2})^{1.105} \times {}^{-(}\frac{813-479.2}{672.2})^{1.105}$$
$$\times {}^{-(}\frac{1628-479.2}{672.2})^{1.105} \times {}^{-(}\frac{1630-479.2}{672.2})^{1.105}$$
$$\times {}^{-(}\frac{677-479.2}{672.2})^{1.105} \tag{5.31}$$

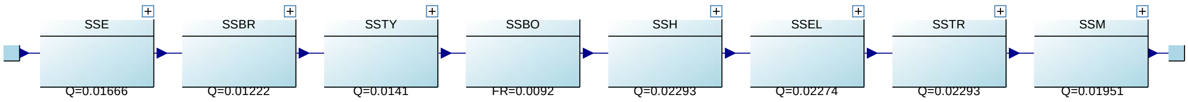
$$_{31}(\ ) = 0.8885 \times 0.6298 \times 0.3609 \times 0.6295 \times 0.2638 \times 0.2633 \times 0.7712 \tag{5.32}$$

$$y \qquad y_{i=1} \times 100$$

$$(\ _{31}) = \prod^{n}$$

$$= 67.24\% \tag{5.33}$$

Study Area-2:



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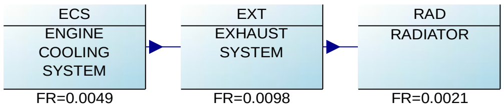
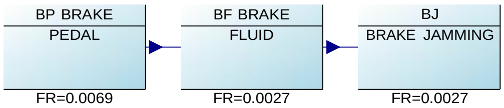


BRAKING SYSTEM:



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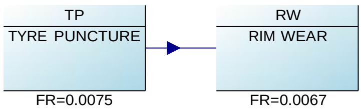
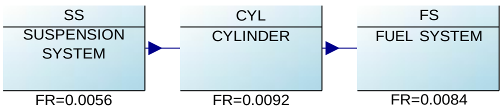
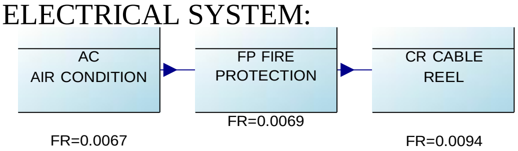


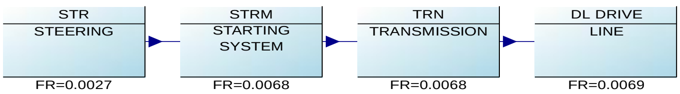
HYDRAULIC SYSTEM:



ELECTRICAL SYSTEM:



TRANSMISSION SYSTEM:



MECHANICAL SYSTEM:

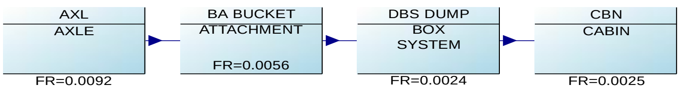
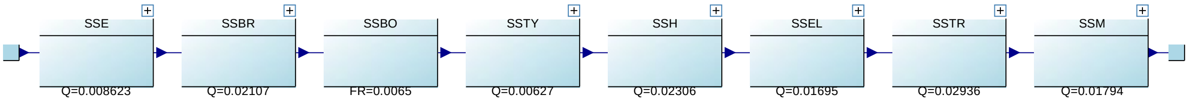
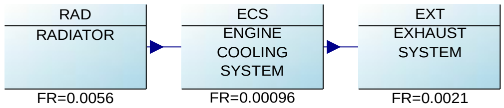


Figure 5.3 Reliability Block Diagram (RBD) of LHD1



ENGINE SYSTEM:



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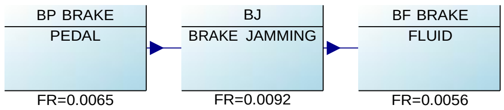

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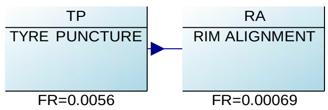
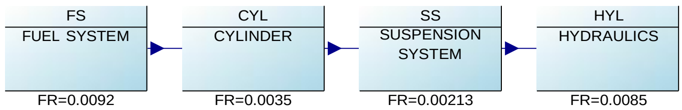
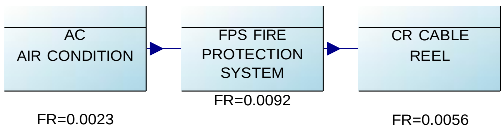


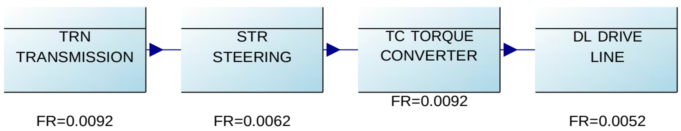
HYDRAULIC SYSTEM:



ELECTRICAL SYSTEM:



TRANSMISSION SYSTEM:



MECHANICAL SYSTEM:

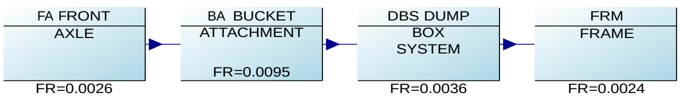


Figure 5.4 Reliability Block Diagram (RBD) of LHD2

Developed mathematical models of RBD for LHDs in study area-2:

$$_{H\ \ 2}(\ \ ) = -(\frac{1340-0}{191.8})^{1.625} \times -(\frac{2683-0}{191.8})^{1.625} \times -(\frac{1338-0}{191.8})^{1.625} \times -(\frac{2684-0}{191.8})^{1.625}$$
$$\times -(\frac{1003-0}{191.8})^{1.625} \times -(\frac{4026-0}{191.8})^{1.625}$$
$$\times -(\frac{1340-0}{191.8})^{1.625} \qquad (5.37)$$

$$_{H\ \ 2}(\ \ ) = 0.6322 \times 0.3804 \times 0.4866 \times 0.6848 \times 0.5734 \times 0.4461$$
$$\times 0.8275 \qquad (5.38)$$

$$y \qquad\qquad y \quad _{i=1} \quad \times 100$$
$$(\ \ _{H\ \ 2}) = \prod^{n}$$
$$= 72.71\% \qquad (5.39)$$

$$_{H\ \ 3}(\ \ ) = -(\frac{2691-487.4}{446.5})^{0.7041} \times -(\frac{2017-487.4}{446.5})^{0.7041} \times -(\frac{1150-487.4}{446.5})^{0.7041}$$
$$\times -(\frac{2690-487.4}{446.5})^{0.7041} \times -(\frac{731-487.4}{446.5})^{0.7041} \times -(\frac{2018-487.4}{446.5})^{0.7041}$$
$$\times -(\frac{1151-487.4}{446.5})^{0.7041} \qquad (5.40)$$

$$_{H\ \ 3}(\ \ ) = 0.7022 \times 0.4716 \times 0.6299 \times 0.6722 \times 0.4564 \times 0.5012$$
$$\times 0.8162 \qquad (5.41)$$

$$y \qquad\qquad y \quad _{i=1} \quad \times 100$$
$$(\ \ _{H\ \ 3}) = \prod^{n}$$
$$= 87.49\% \qquad (5.42)$$

$$_{H\ \ 4}(\ \ ) = -(\frac{1150-0}{159.5})^{2.048} \times -(\frac{2012-0}{159.5})^{2.048} \times -(\frac{1602-0}{159.5})^{2.048} \times -(\frac{1342-0}{159.5})^{2.048}$$
$$\times -(\frac{665-0}{159.5})^{2.048} \times -(\frac{2014-0}{159.5})^{2.048}$$
$$\times -(\frac{800-0}{159.5})^{2.048} \qquad (5.43)$$

$$_{H\ \ 4}(\ \ ) = 0.6190 \times 0.4978 \times 0.6031 \times 0.6555 \times 0.4606 \times 0.4851$$
$$\times 0.7988 \qquad (5.44)$$

$$y \qquad\qquad y \quad _{i=1} \quad \times 100$$
$$(\ \ _{H\ \ 4}) = \prod^{n}$$
$$= 84.48\% \qquad (5.45)$$

$$_{H\ \ 5}(\ \ ) = -(\frac{1150-0}{159.5})^{2.048} \times -(\frac{2012-0}{159.5})^{2.048} \times -(\frac{1602-0}{159.5})^{2.048} \times -(\frac{1342-0}{159.5})^{2.048}$$
$$\times -(\frac{665-0}{159.5})^{2.048} \times -(\frac{2014-0}{159.5})^{2.048}$$
$$\times -(\frac{800-0}{159.5})^{2.048} \qquad (5.46)$$

$$_{H\ \ 5}(\ \ ) = 0.6855 \times 0.6624 \times 0.6148 \times 0.6638 \times 0.4688 \times 0.4066$$
$$\times 0.6061 \qquad (5.47)$$

$$y \qquad\qquad y \quad _{i=1} \quad \times 100$$
$$(\ \ _{H\ \ 5}) = \prod^{n}$$
$$= 85.29\% \qquad (5.48)$$

Table 5.2 Reliability results (R in %) of each individual sub-system of study area-2

Machine	Sub-system Reliability							Sys. Reliability, Rs (%)
	SS E	SS Br	SS Ty	SS H	SS El	SS Tr	SS M	
LHD1	53.73	34.92	79.44	49.42	32.68	63.76	53.77	64.77
LHD2	63.22	38.04	48.66	68.48	57.34	44.61	82.75	72.71
LHD3	70.22	47.16	62.99	67.22	45.64	50.12	81.62	87.49
LHD4	61.90	49.78	60.31	65.55	46.06	48.51	79.88	84.48
LHD5	68.55	66.24	61.48	66.38	46.88	40.66	60.61	85.29

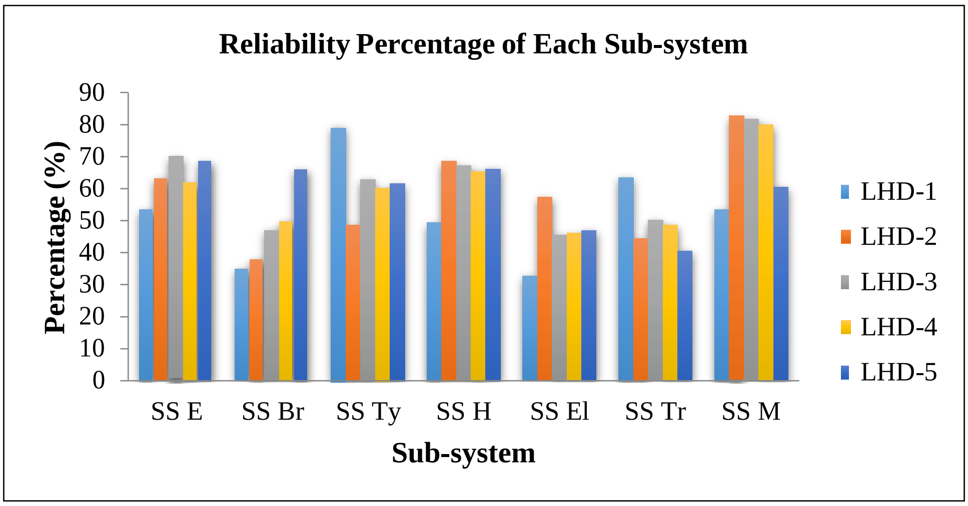


Figure 5.9 Reliability Percentage of Each Sub-system of LHDs of study area-2

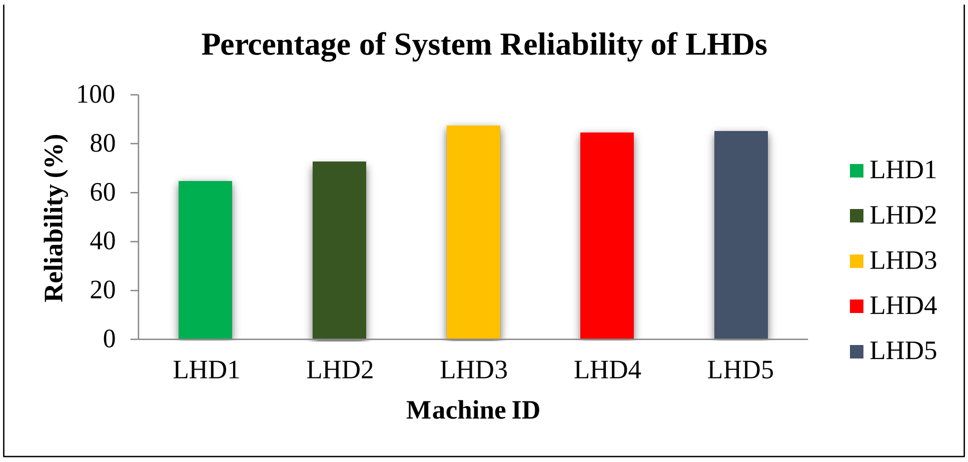
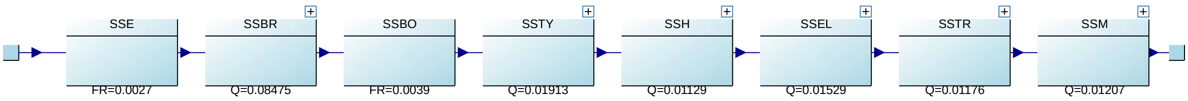
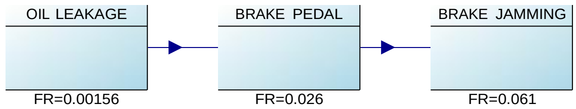


Figure 5.10 Percentage of System reliabilities of LHDs of Study Area-2

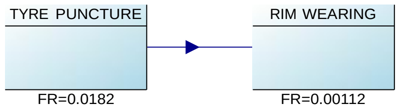
Study area-3



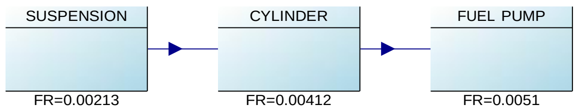
BRAKING SYSTEM



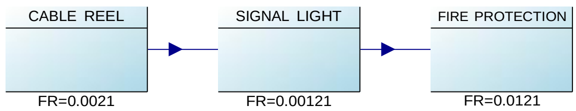
TYRE OR WHEEL SYSTEM



HYDRAULIC SYSTEM



ELECTRICAL SYSTEM



MECHANICAL SYSTEM

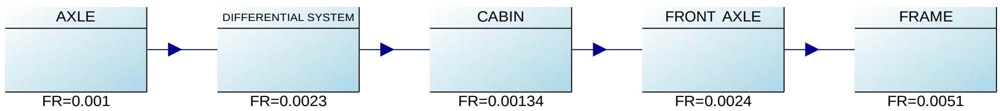
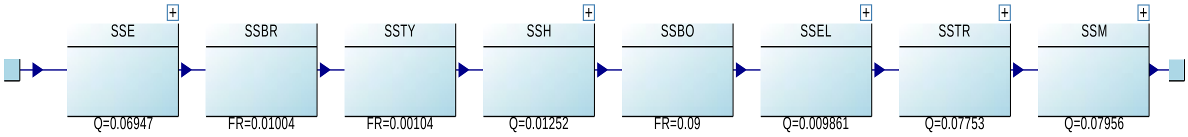
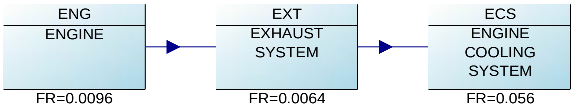


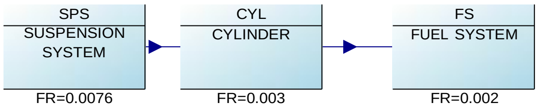
Figure 5.5 Reliability Block Diagram (RBD) of E1-LHD1



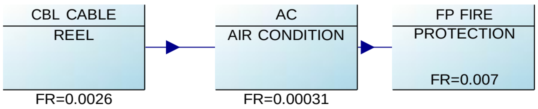
ENGINE SYSTEM:



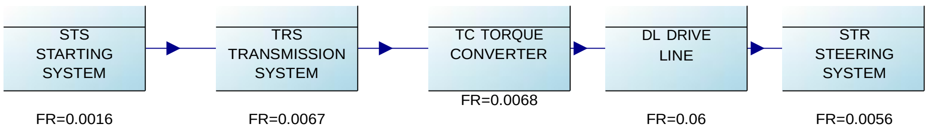
HYDRAULIC SYSTEM:



ELECTRICAL SYSTEM:



TRANSMISSION SYSTEM:



MECHANICAL SYSTEM:

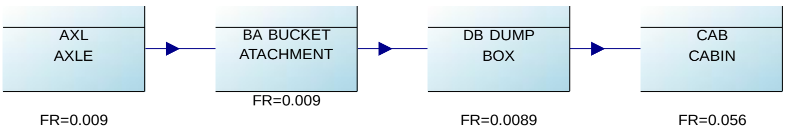


Figure 5.6 Reliability Block Diagram (RBD) of E2-LHD2

Developed mathematical models of RBD for LHDs in study area-2:

$$_{2-H\ 2}(\ ) = -\left(\frac{644+4.245}{208.3}\right)^{1.802} \times -\left(\frac{979+4.245}{208.3}\right)^{1.802} \times -\left(\frac{558+4.245}{208.3}\right)^{1.802}$$
$$\times -\left(\frac{341+4.245}{208.3}\right)^{1.802} \times -\left(\frac{259+4.245}{208.3}\right)^{1.802} \times -\left(\frac{785+4.245}{208.3}\right)^{1.802}$$
$$\times -\left(\frac{155+4.245}{208.3}\right)^{1.802} \qquad (5.52)$$

$$_{2-H\ 2}(\ ) = 0.7522 \times 0.2234 \times 0.4964 \times 0.7022 \times 0.8067 \times 0.5112 \times 0.4999 \qquad (5.53)$$

$$y \quad (\ _{2-H\ 2}) = \prod_{i=1}^{n} y \times 100 = 69.82\% \qquad (5.54)$$

$$_{3-H\ 3}(\ ) = -\left(\frac{845+93.92}{233.3}\right)^{3.264} \times -\left(\frac{1129+93.92}{233.3}\right)^{3.264} \times -\left(\frac{478+93.92}{233.3}\right)^{3.264}$$
$$\times -\left(\frac{676+93.92}{233.3}\right)^{3.264} \times -\left(\frac{183+93.92}{233.3}\right)^{3.264} \times -\left(\frac{676+93.92}{233.3}\right)^{3.264}$$
$$\times -\left(\frac{181+93.92}{233.3}\right)^{3.264} \qquad (5.55)$$

$$_{3-H\ 3}(\ ) = 0.6922 \times 0.3834 \times 0.4099 \times 0.7222 \times 0.8167 \times 0.5122 \times 0.5564 \qquad (5.56)$$

$$y \quad (\ _{3-H\ 3}) = \prod_{i=1}^{n} y \times 100 = 88.09\% \qquad (5.57)$$

$$_{5-H\ 5}(\ ) = -\left(\frac{535-24.75}{70.48}\right)^{0.668} \times -\left(\frac{1254-24.75}{70.48}\right)^{0.668} \times -\left(\frac{264-24.75}{70.48}\right)^{0.668}$$
$$\times -\left(\frac{940-24.75}{70.48}\right)^{0.668} \times -\left(\frac{202-24.75}{70.48}\right)^{0.668} \times -\left(\frac{1879-24.75}{70.48}\right)^{0.668}$$
$$\times -\left(\frac{222-24.75}{70.48}\right)^{0.668} \qquad (5.58)$$

$$_{5-H\ 5}(\ ) = 0.7022 \times 0.4999 \times 0.2234 \times 0.7564 \times 0.7967 \times 0.5112 \times 0.4867 \qquad (5.59)$$

$$y \quad (\ _{5-H\ 5}) = \prod_{i=1}^{n} y \times 100 = 68.87\% \qquad (5.60)$$

$$_{6-H\ 6}(\ ) = -\left(\frac{977+437.4}{570.9}\right)^{10.16} \times -\left(\frac{782+437.4}{570.9}\right)^{10.16} \times -\left(\frac{648+437.4}{570.9}\right)^{10.16}$$
$$\times -\left(\frac{781+437.4}{570.9}\right)^{10.16} \times -\left(\frac{188+437.4}{570.9}\right)^{10.16} \times -\left(\frac{1307+437.4}{570.9}\right)^{10.16}$$
$$\times -\left(\frac{215+437.4}{570.9}\right)^{10.16} \qquad (5.61)$$

$$_{6-H\ 6}(\ ) = 0.5112 \times 0.3734 \times 0.4099 \times 0.7222 \times 0.8167 \times 0.6922 \times 0.5016 \qquad (5.62)$$

$$y \qquad y \quad {}_{i=1} \quad \times 100$$

$$(\quad {}_{6-} \; {}_{H} \; {}_{6}) = \prod^{n}$$

$$= 87.80\% \qquad (5.63)$$

Table 5.3 Reliability results (R in %) of each individual sub-system of study area-3

Machine	Sub-system Reliability							Sys. Reliability, Rs (%)
	SS E	SS Br	SS Ty	SS H	SS El	SS Tr	SS M	
E1-LHD1	69.22	38.34	40.99	72.22	81.67	51.12	55.64	84.77
E2-LHD2	75.22	22.34	49.64	70.22	80.67	51.12	49.99	69.82
E3-LHD3	69.22	38.34	40.99	72.22	81.67	51.12	55.64	88.09
E5-LHD5	70.22	49.99	22.34	75.64	79.67	51.12	48.67	68.87
E6-LHD6	51.12	37.34	40.99	72.22	81.67	69.22	50.16	87.80

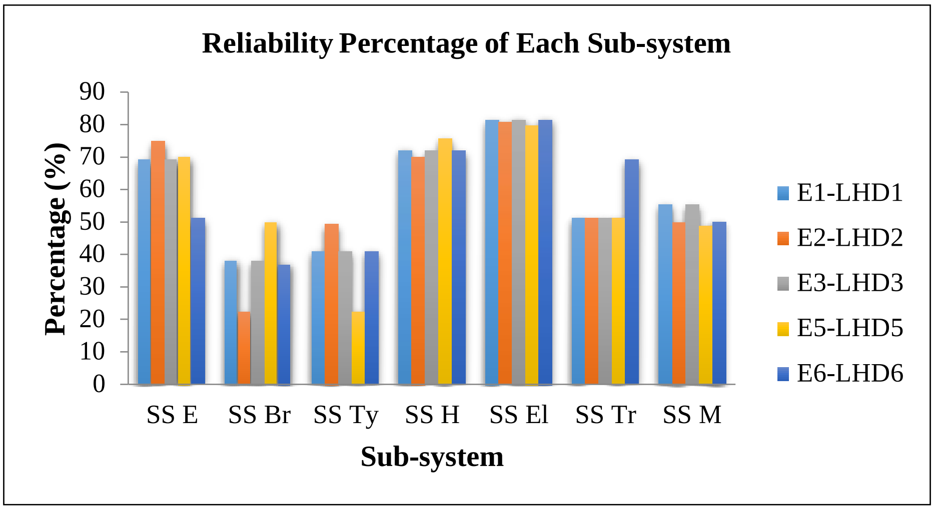


Figure 5. 11 Reliability percentage of each sub-system of LHDs of study area-3

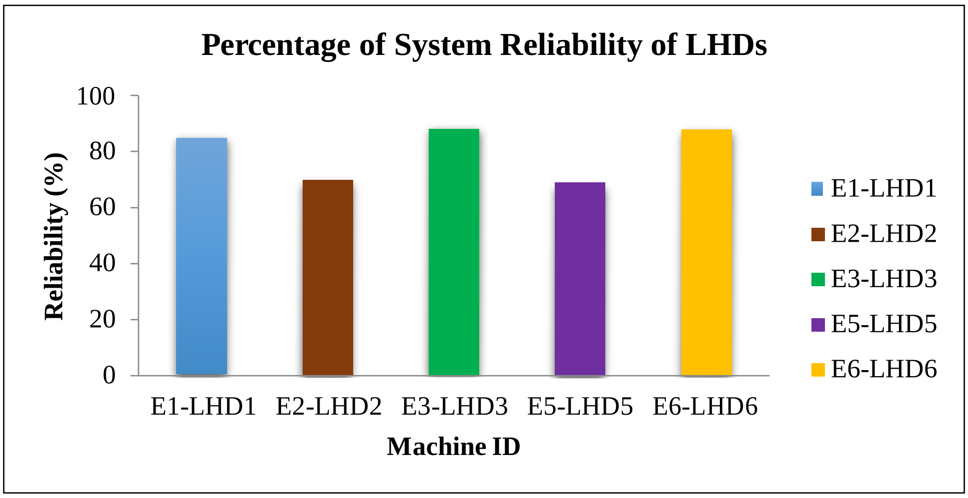


Figure 5.12 Percentage of system reliabilities of LHDs of Study Area-3

- **Block Time Profiles of study area-1**

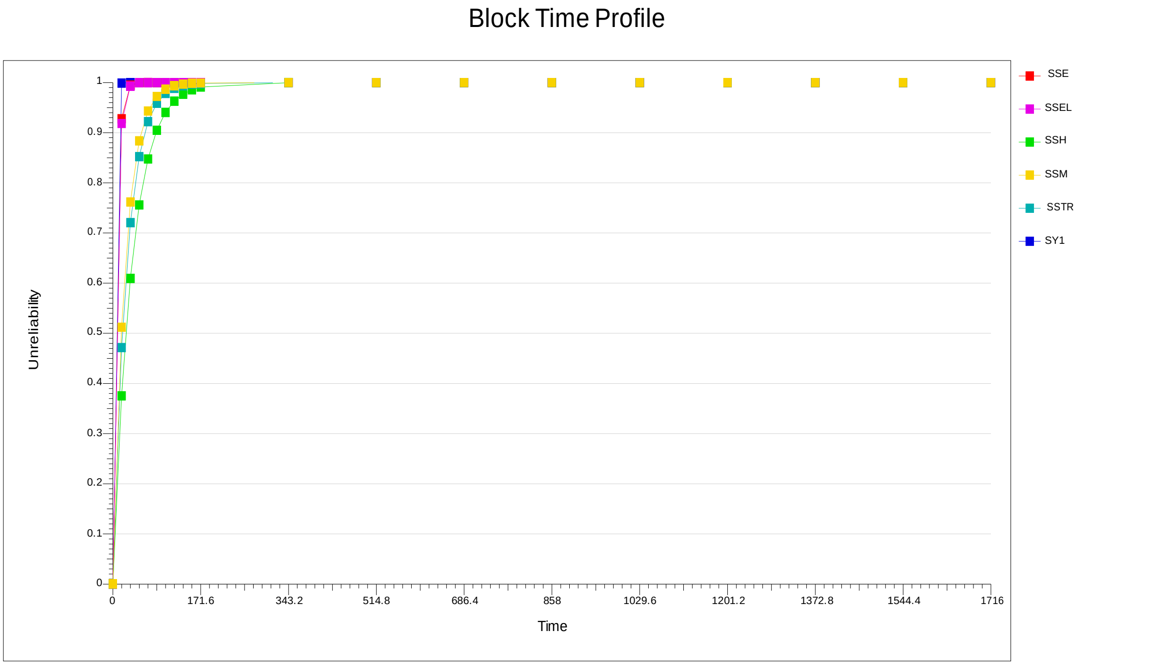


Figure 5.14 System un-reliability of LH22 of study area-1

- **Block Time Profiles of study area-2**

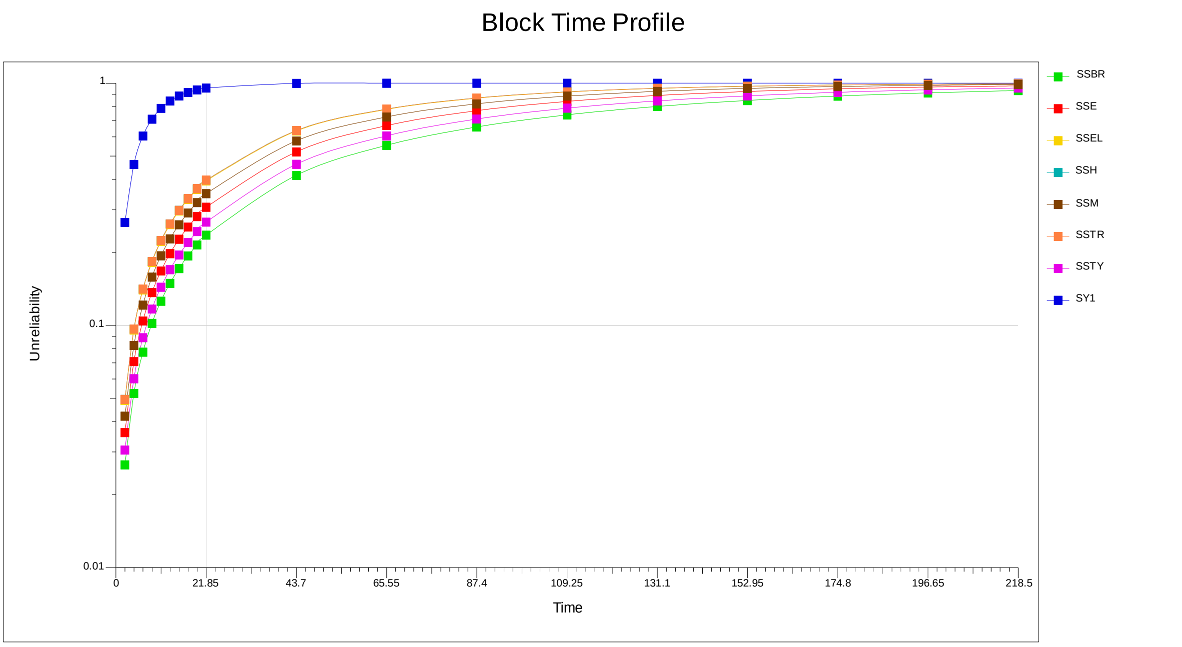


Figure 5.15 System un-reliability of LHD1 of study area-2

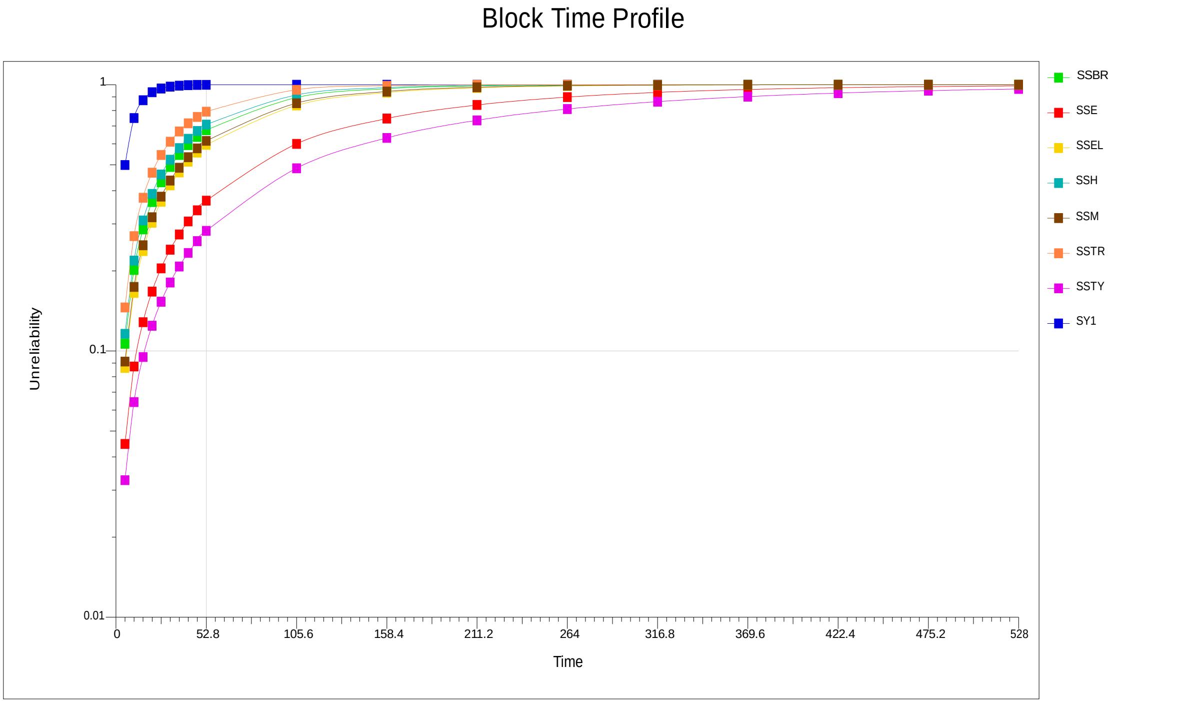


Figure 5.16 System un-reliability of LHD2 of study area-2

- **Block Time Profile of study area-3:**

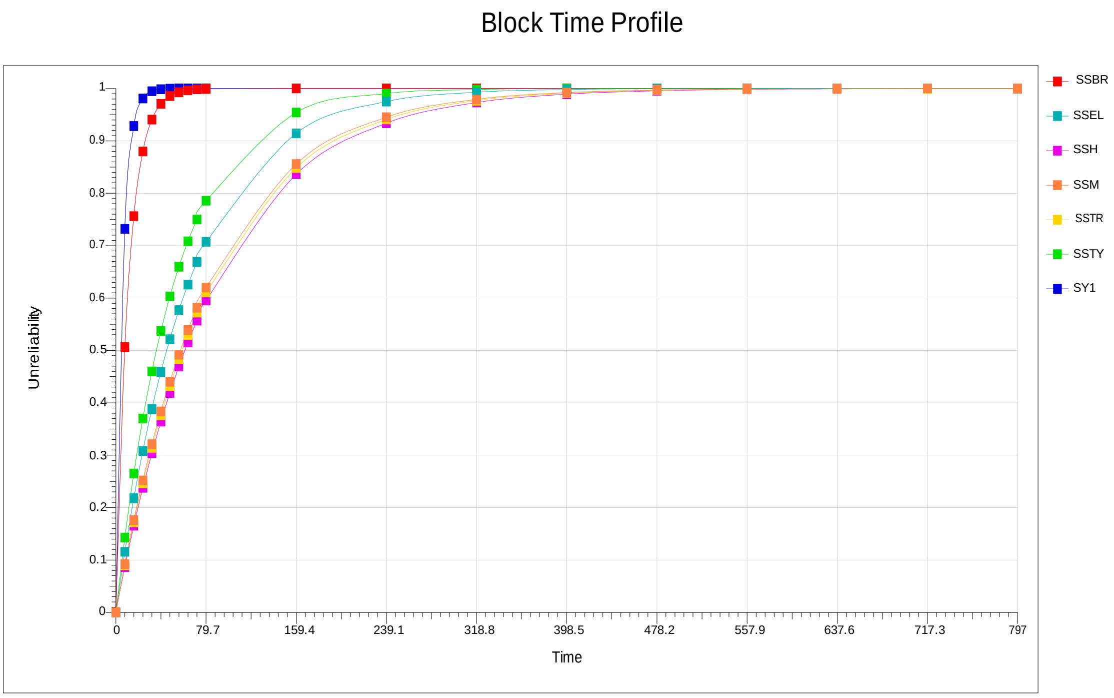


Figure 5.17 System un-reliability of E1-LHD1 of study area-3

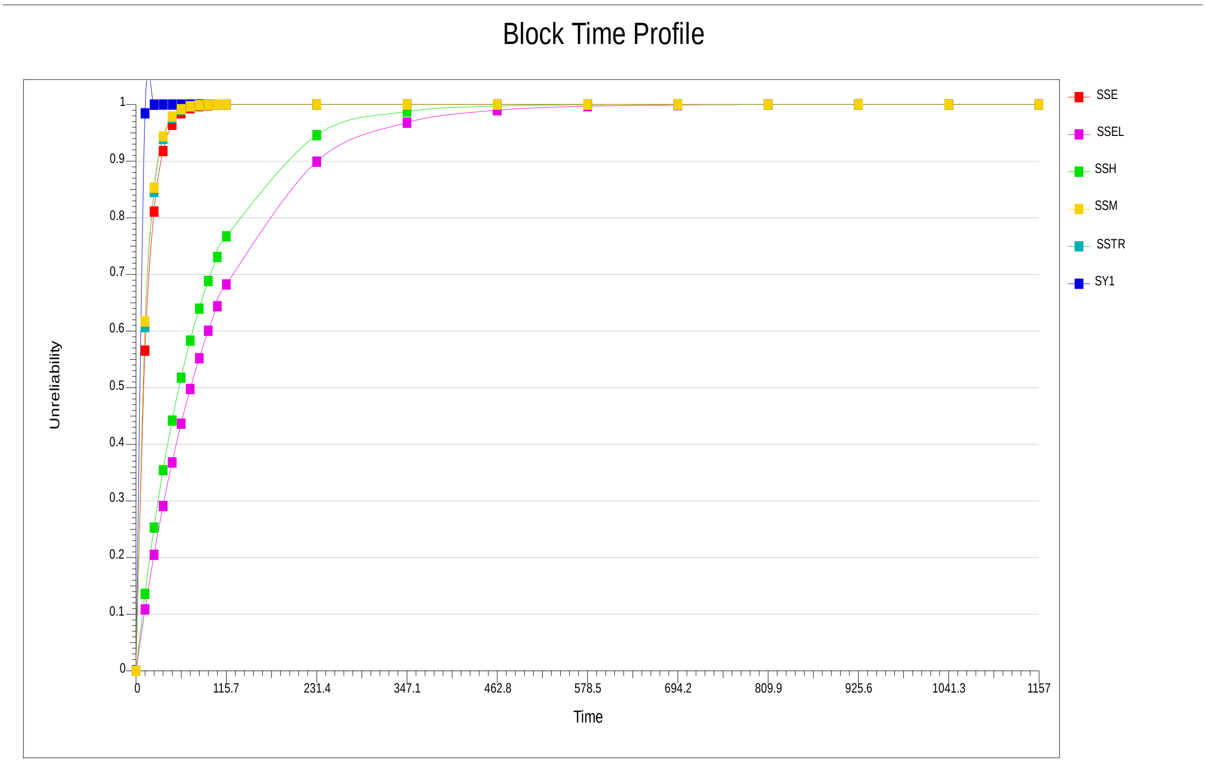


Figure 5.18 System un-reliability of E2-LHD2 of study area-3

- **Fussell-Vesely Importance of study area-1:**

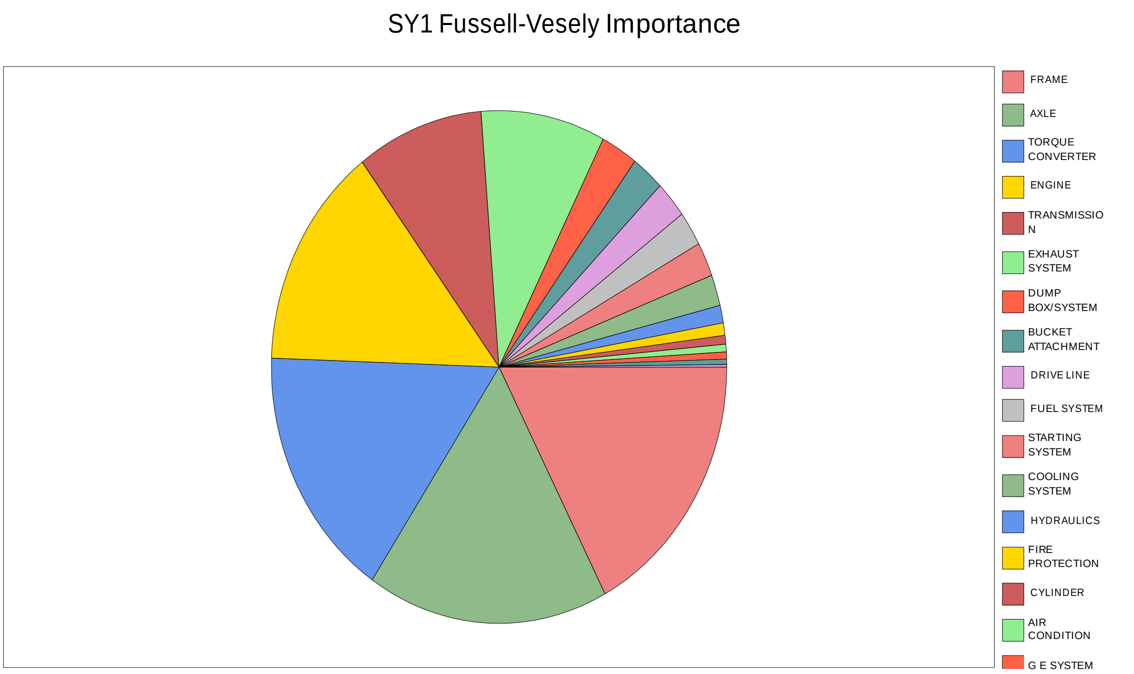


Figure 5.20 Fussell-Vesely Importance of LH22 of study area-1

- **Fussell-Vesely Importance of study area-2**

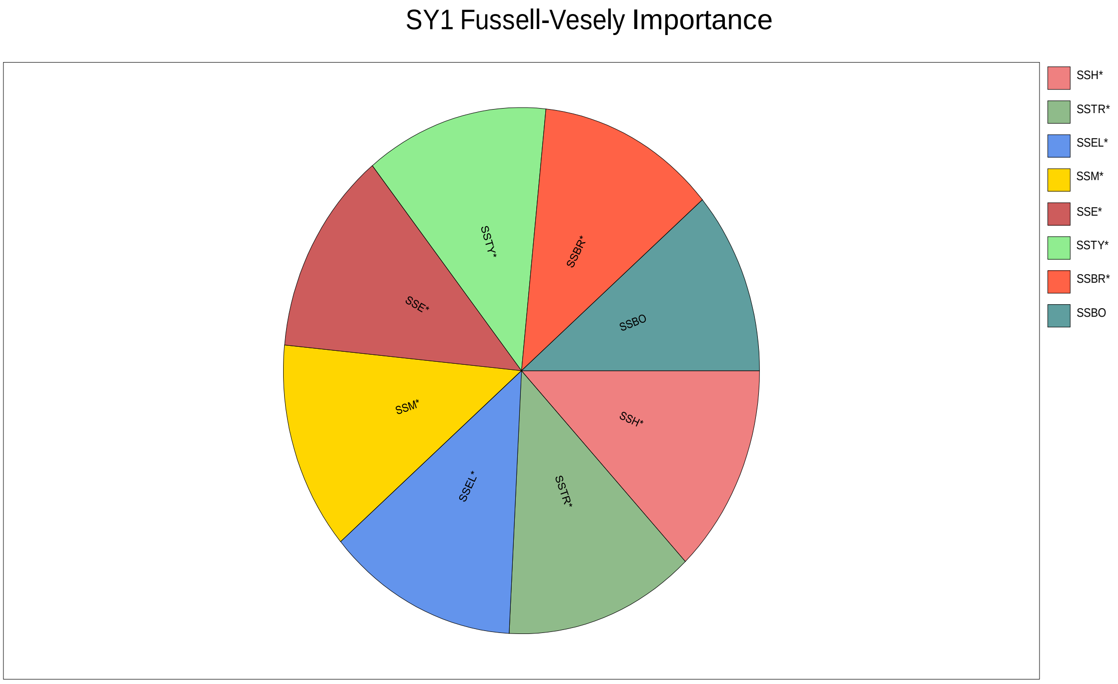


Figure 5.21 Fussell-Vesely Importance of LHD1 of study area-2

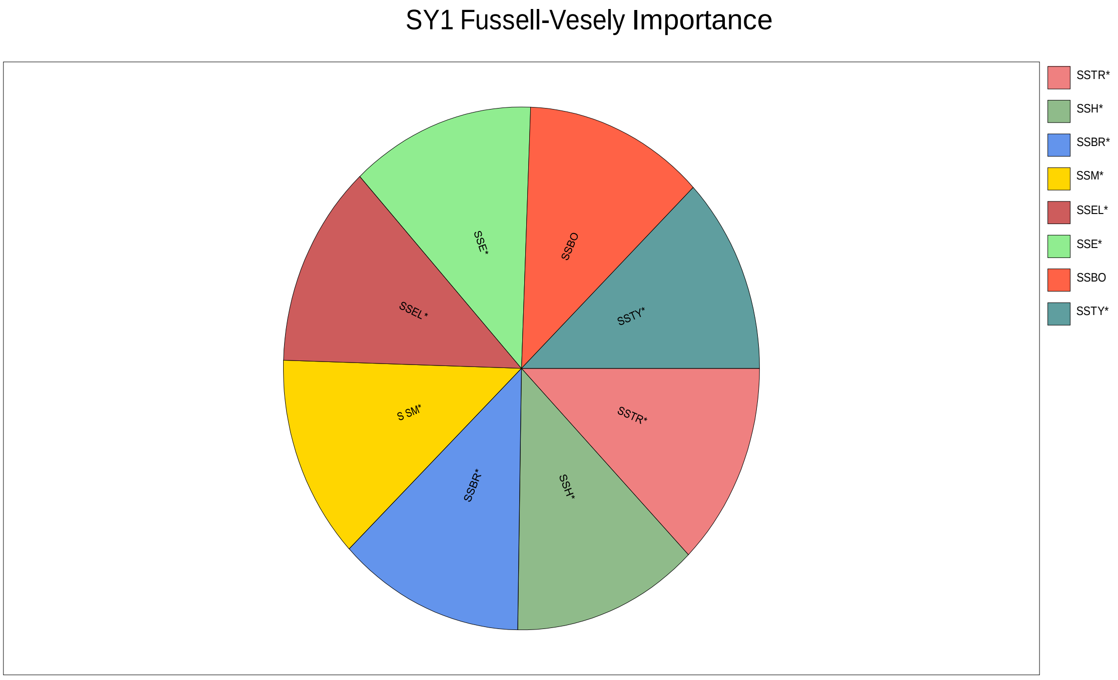


Figure 5.22 Fussell-Vesely Importance of LHD2 of study area-2

- **Fussell-Vesely Importance of study area-3**

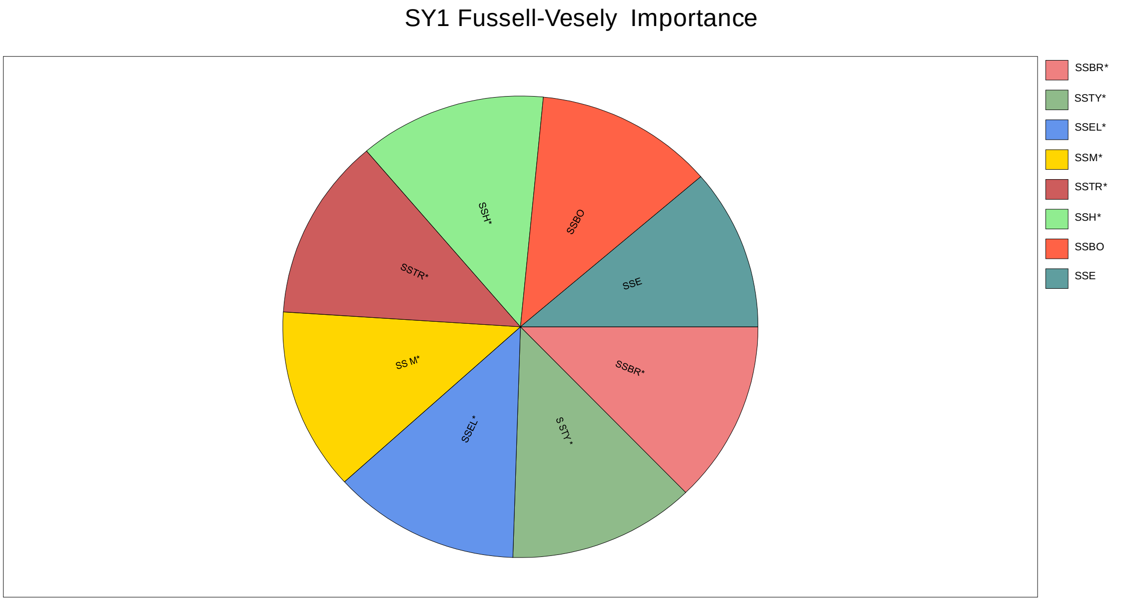


Figure 5.23 Fussell-Vesely Importance of E1-LHD1 of study area-3

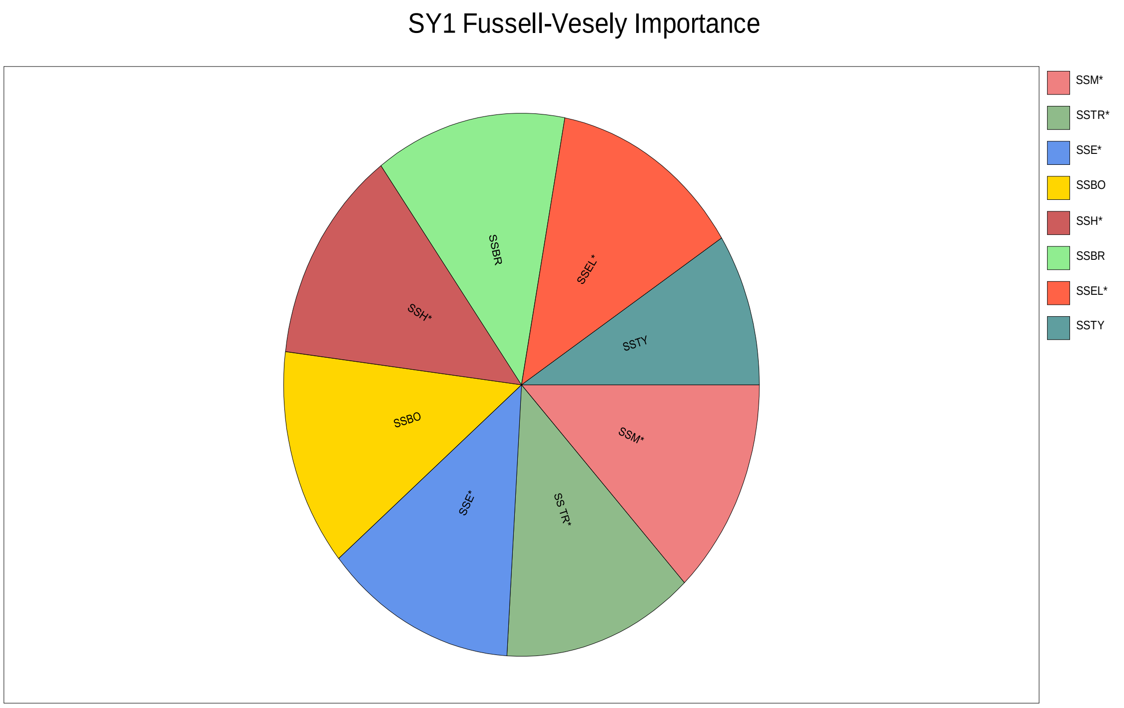


Figure 5.24 Fussell-Vesely Importance of E2-LHD2 of study area-3

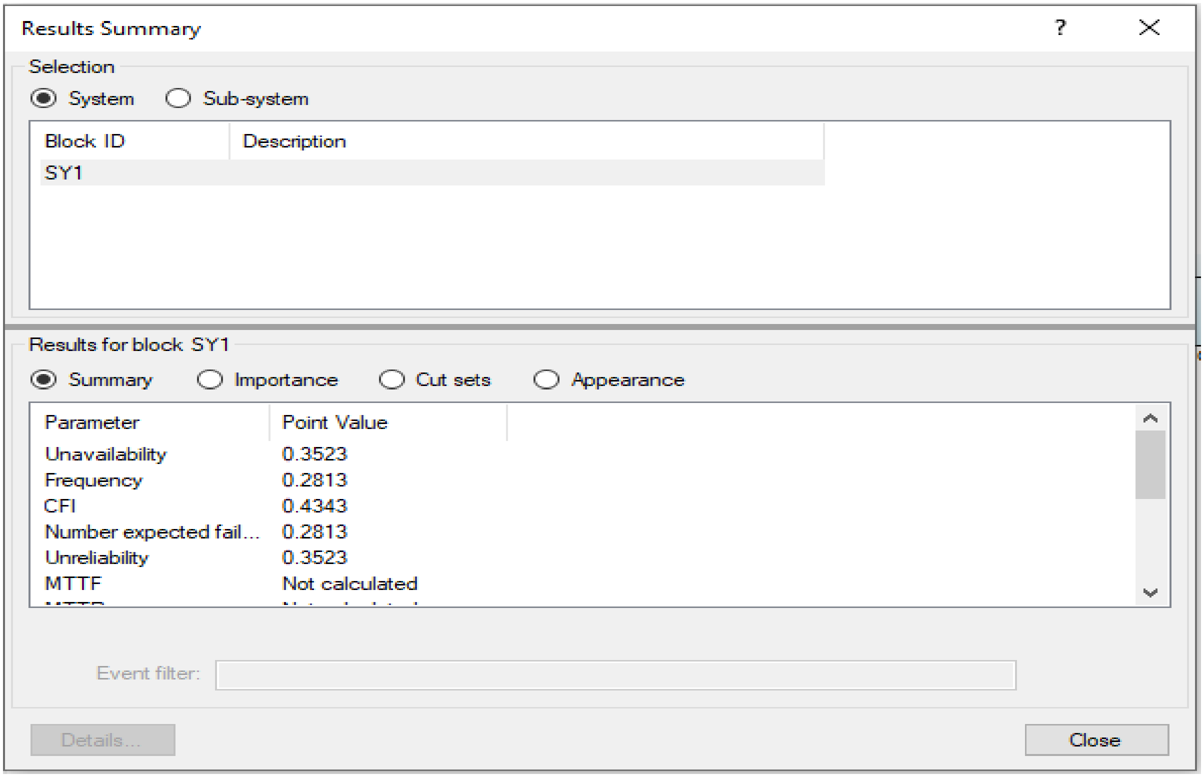


Figure 5.26 An example of results summery screenshot for LHD1 of study area-2

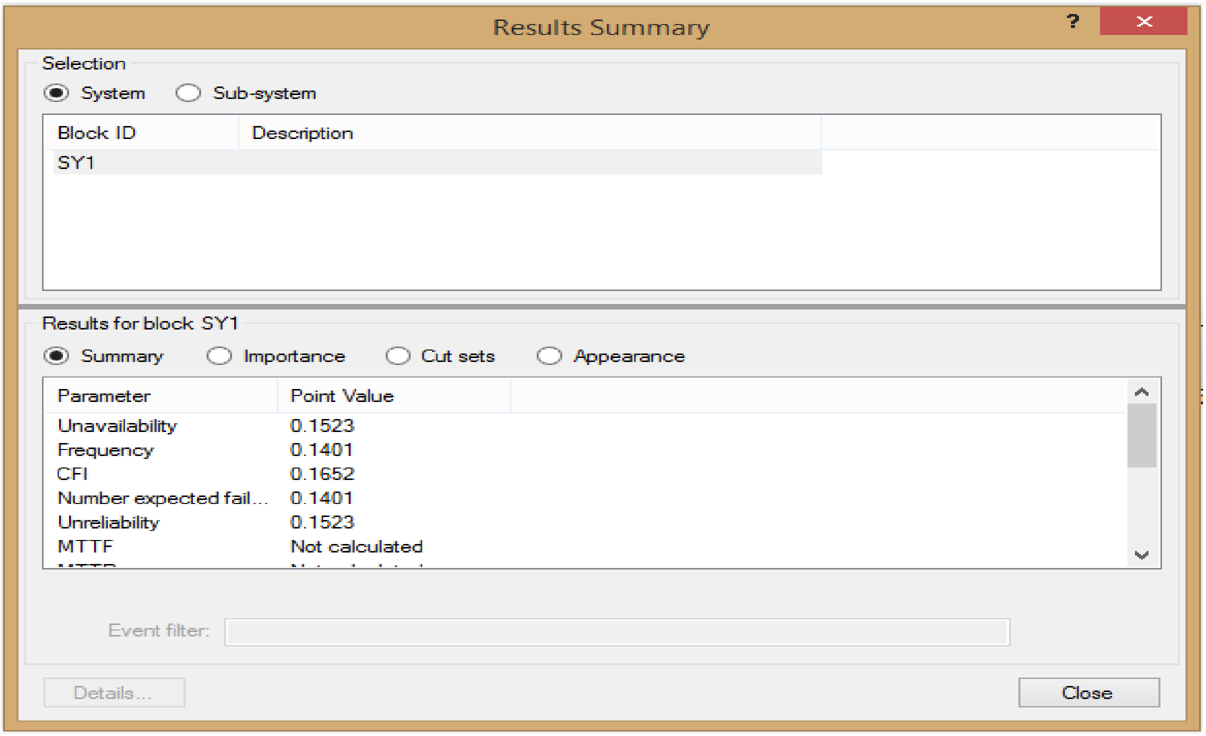


Figure 5.27 An example of results summery E1-LHD1 screenshot of study area-3

Table 5.5 Results of reliable life for each individual LHD of study area-2

Machine	System Reliability, Rs	Best Fit Distribution	Scale Parameter, η	Shape Parameter, β	Location Parameter, γ	Reliable Life, T_R(hours)
LHD1	64.77	Weibull 3P	29.88	0.8365	68.3	233.04
LHD2	72.71	Weibull 2P	191.8	1.625	0	469.71
LHD3	87.49	Weibull 3P	446.5	0.7041	487.4	4233.96
LHD4	84.48	Weibull 2P	159.5	2.048	0	330.14
LHD5	85.29	Weibull 2P	245.9	1.912	0	536.60

Table 5.6 Results of reliable life for each individual LHD of study area-3

Machine	System Reliability, Rs	Best Fit Distribution	Scale Parameter, η	Shape Parameter, β	Location Parameter, γ	Reliable Life, T_R(hours)
E1-LHD1	84.77	Weibull 2P	162.9	1.541	0	428.57
E2-LHD2	69.82	Weibull 3P	208.3	1.802	-4.245	460.45
E3-LHD3	88.09	Weibull 3P	233.3	3.264	-93.92	275.38
E5-LHD5	68.87	Weibull 3P	70.48	0.668	24.75	635.75
E6-LHD6	87.80	Weibull 3P	570.9	10.16	-437.4	224.22

Fault tree diagrams of study area-1

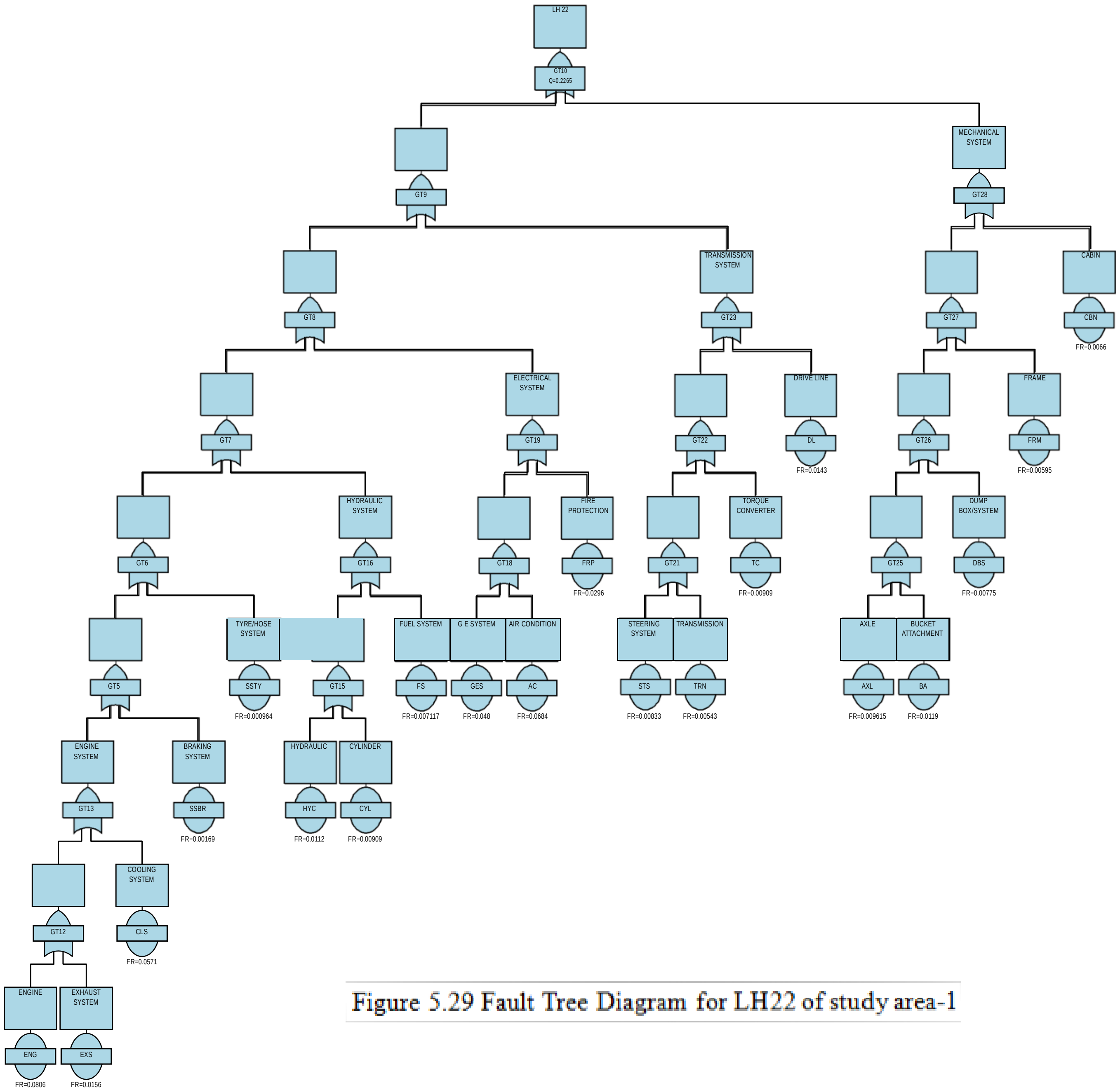


Figure 5.29 Fault Tree Diagram for LH22 of study area-1

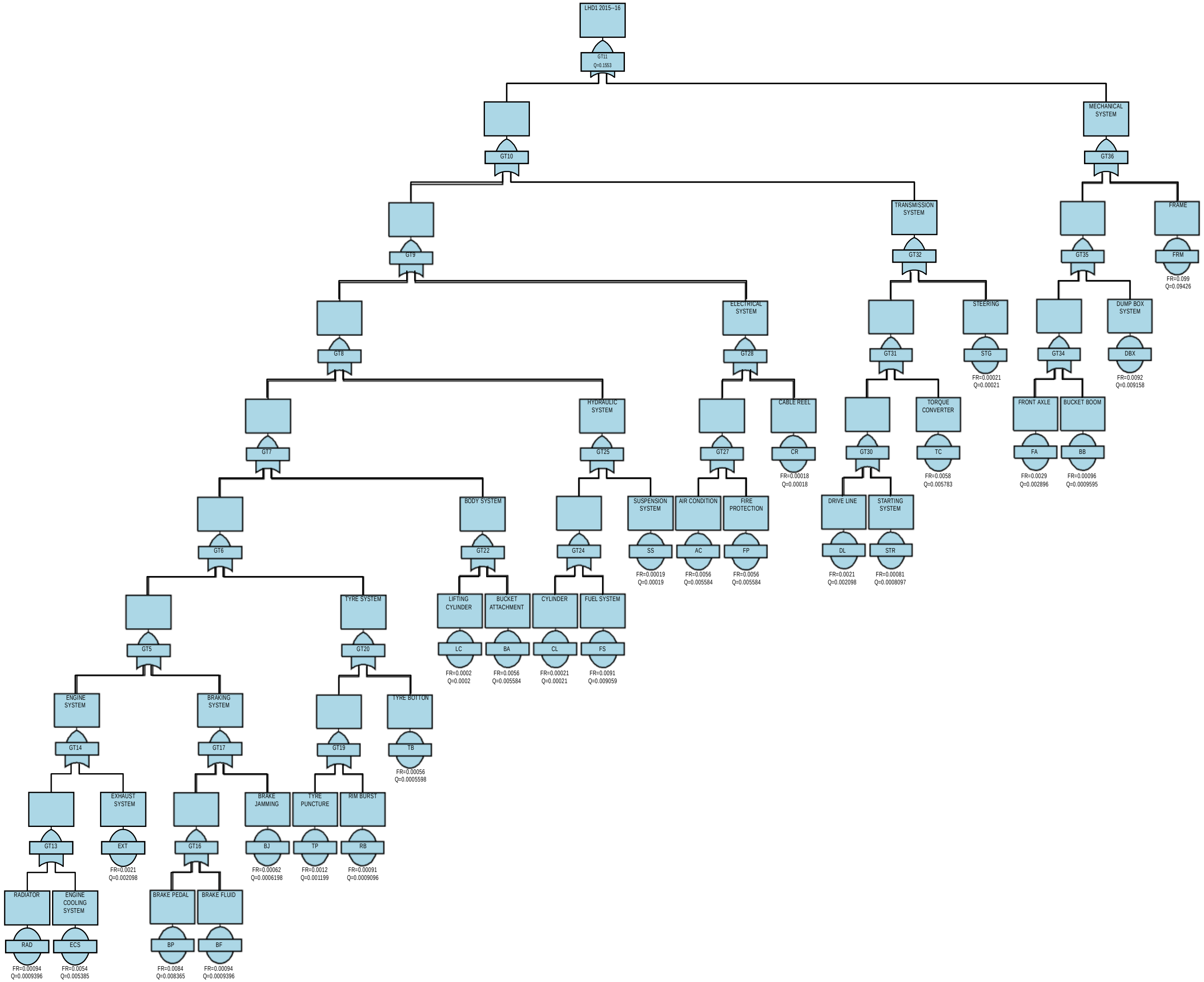


Figure 5.30 Fault Tree Diagram for LHD1 of study area-2

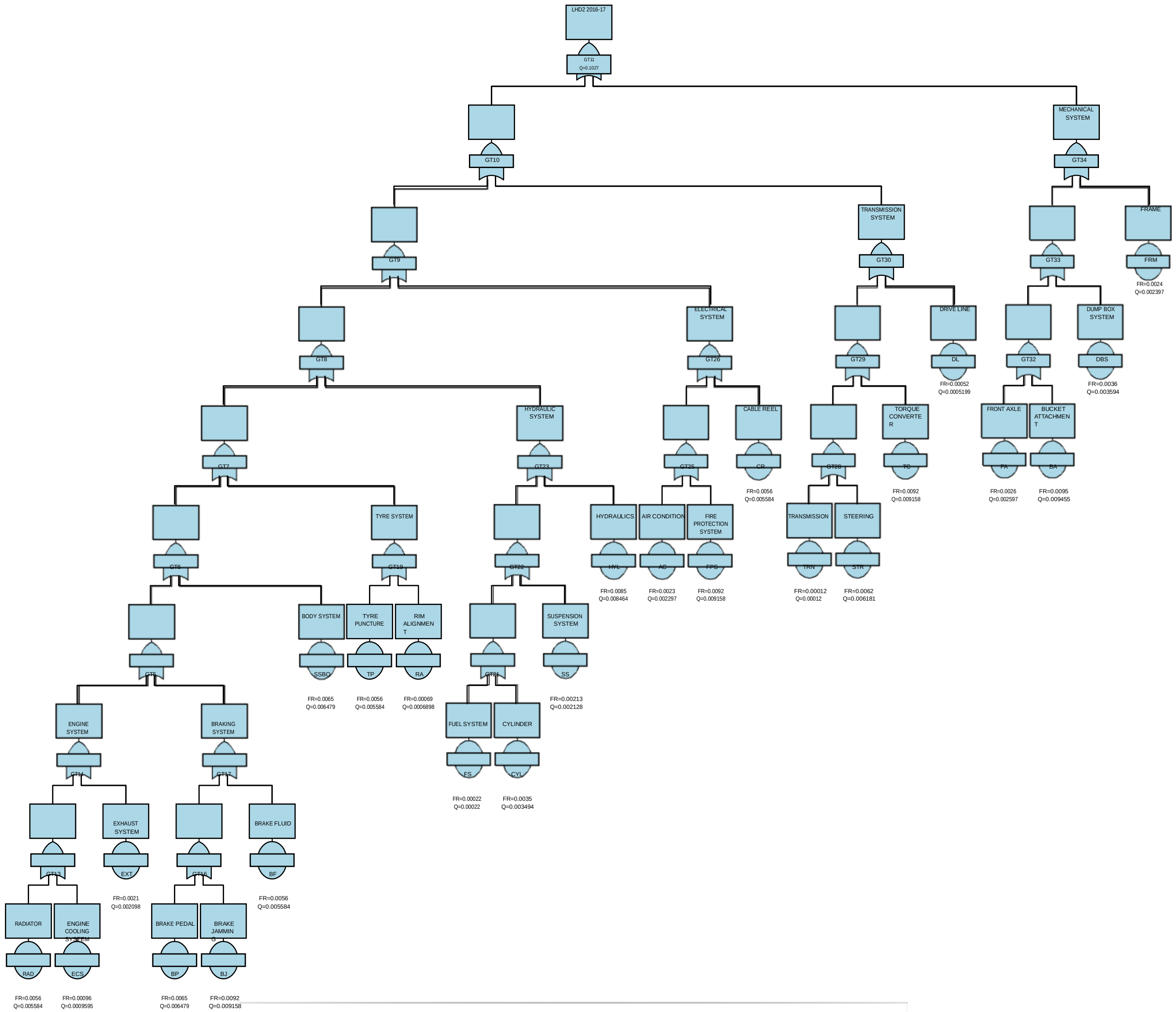


Figure 5.31 Fault Tree Diagram for LHD2 of study area-2

- **Fault tree diagrams of study area-3**

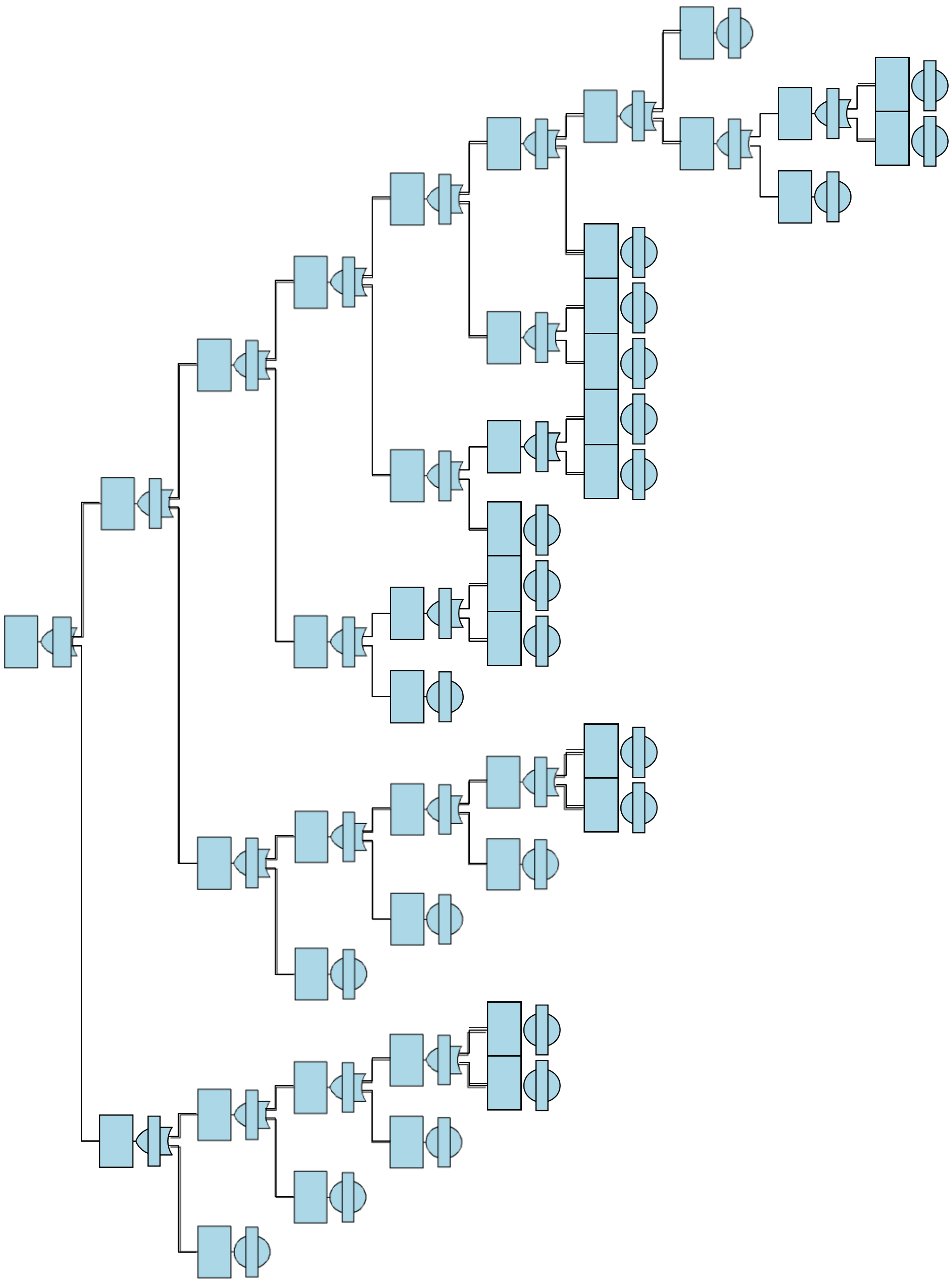


Figure 5.32 Fault Tree Diagram for E1-LHD1 of study area-3

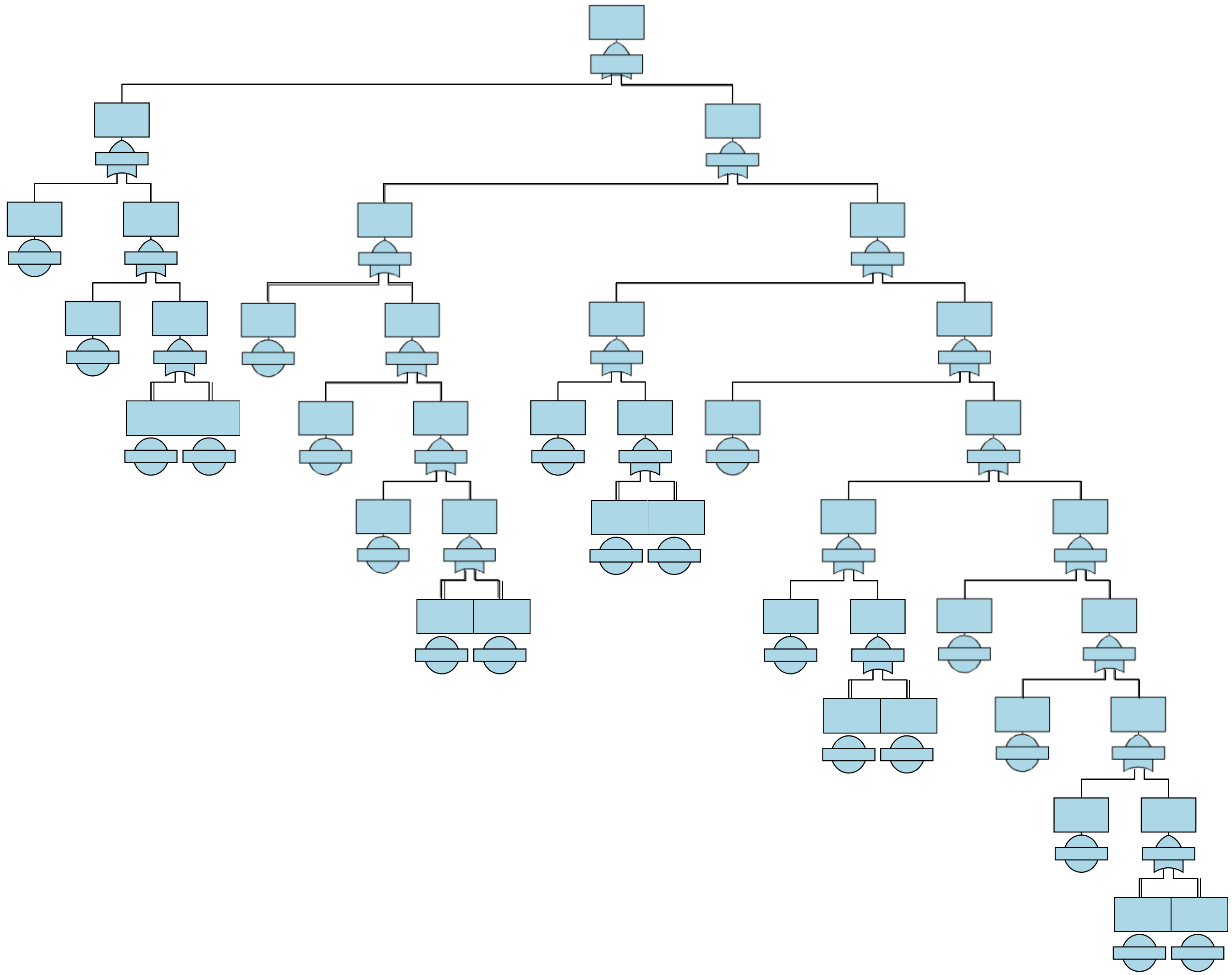


Figure 5.33 Fault Tree Diagram for E2-LHD2 of study area-3

Table 5.8 Percentage of overall system availability of LHDs for study area-2

Machine	MTBF (hours)	MTTR (hours)	Computed Availability (%)	Software Provided Availability (%)	Percentage of Variation (%)
LHD1	101.47	10.7	91.53	84.47	7.06
LHD2	112.7	16.07	92.39	91.02	1.37
LHD3	459.45	234.5	97.7	89.59	8.11
LHD4	190.56	18.51	85.9	84.22	1.68
LHD5	485.81	45.54	97.12	90.40	6.72

Table 5.9 Percentage of overall system availability of LHDs for study area-3

Machine	MTBF (hours)	MTTR (hours)	Computed Availability (%)	Software Provided Availability (%)	Percentage of Variation (%)
E1-LHD1	72.68	16.59	84.94	84.77	0.17
E2-LHD2	64.35	19.24	69.48	69.68	0.2
E3-LHD3	85.48	14.74	87.45	87.92	0.47
E5-LHD5	84.58	11.12	88.82	88.18	0.64
E6-LHD6	87.38	13.27	87.42	87.09	0.33

- **Gate time profile of study area-1:**

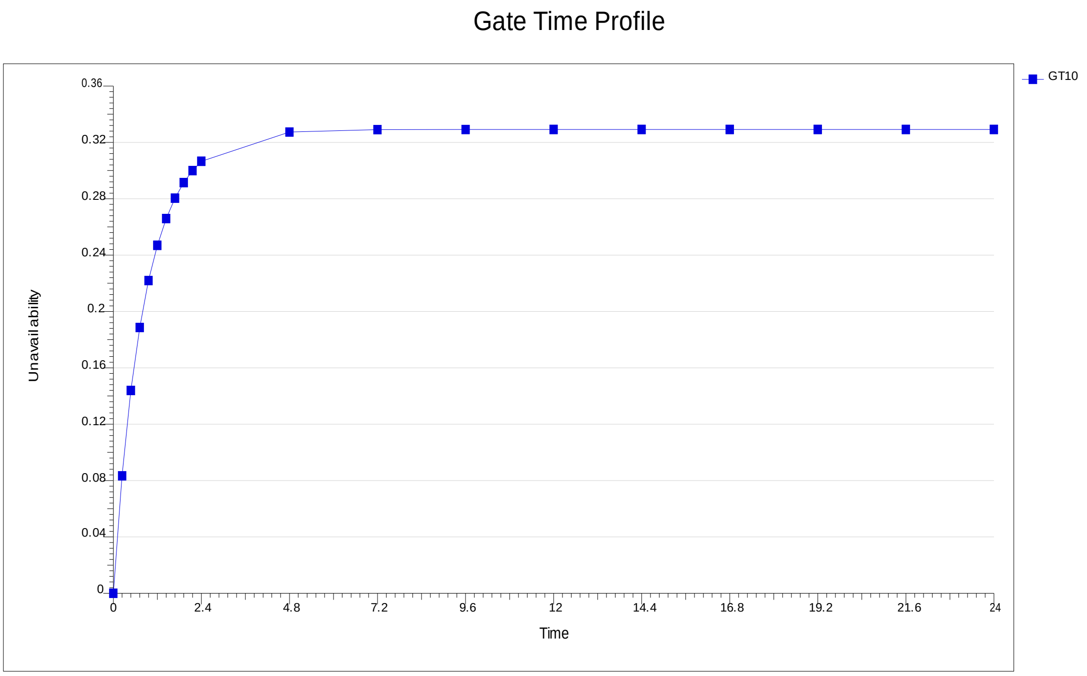


Figure 5.35 Gate time profile of un-availability of LH22

- **Gate time profiles of study area-2:**

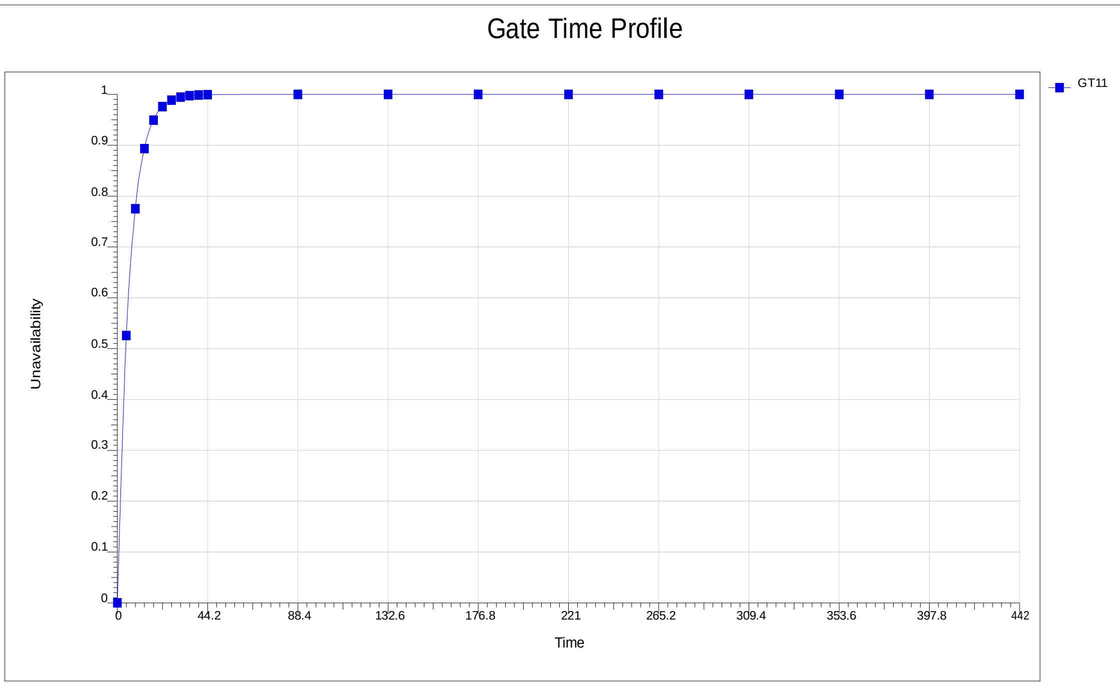


Figure 5.36 Gate time profile of un-availability of LHD1

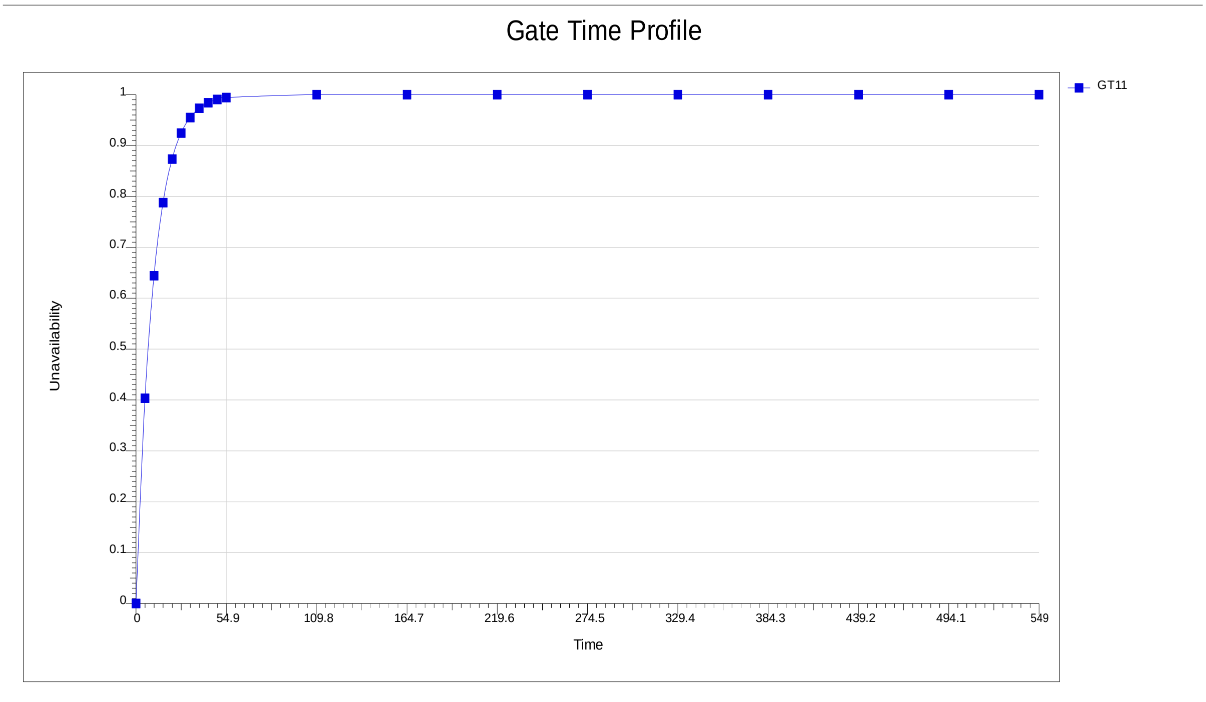


Figure 5.37 Gate time profile of un-availability of LHD2

Gate time profile of steady area-3:

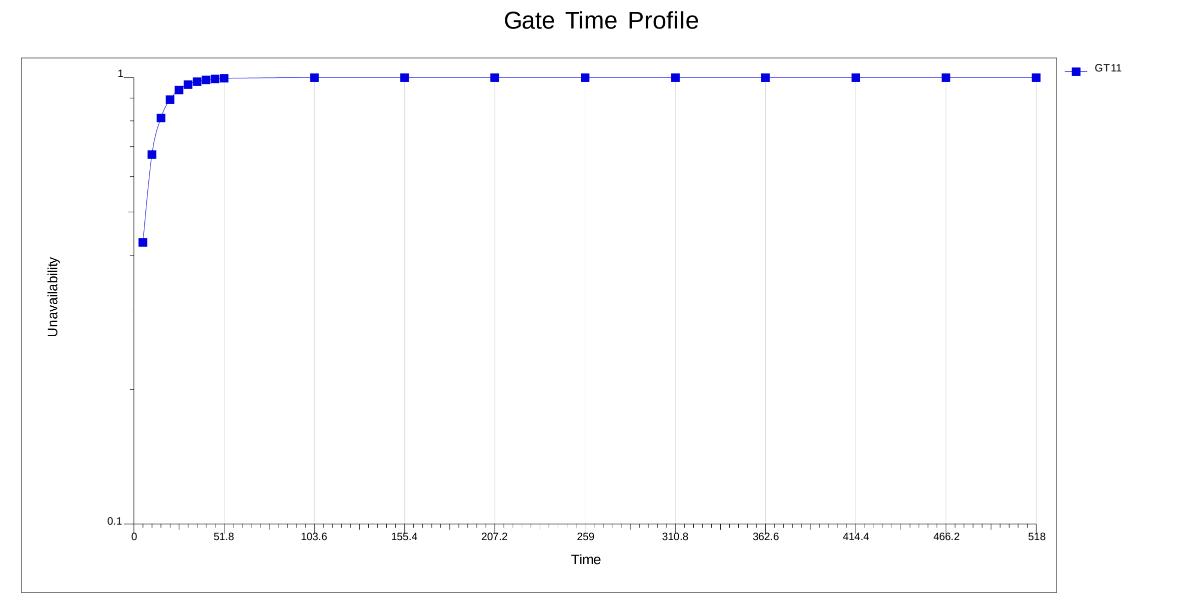


Figure 5.38 Gate time profile of un-availability of E1-LHD1

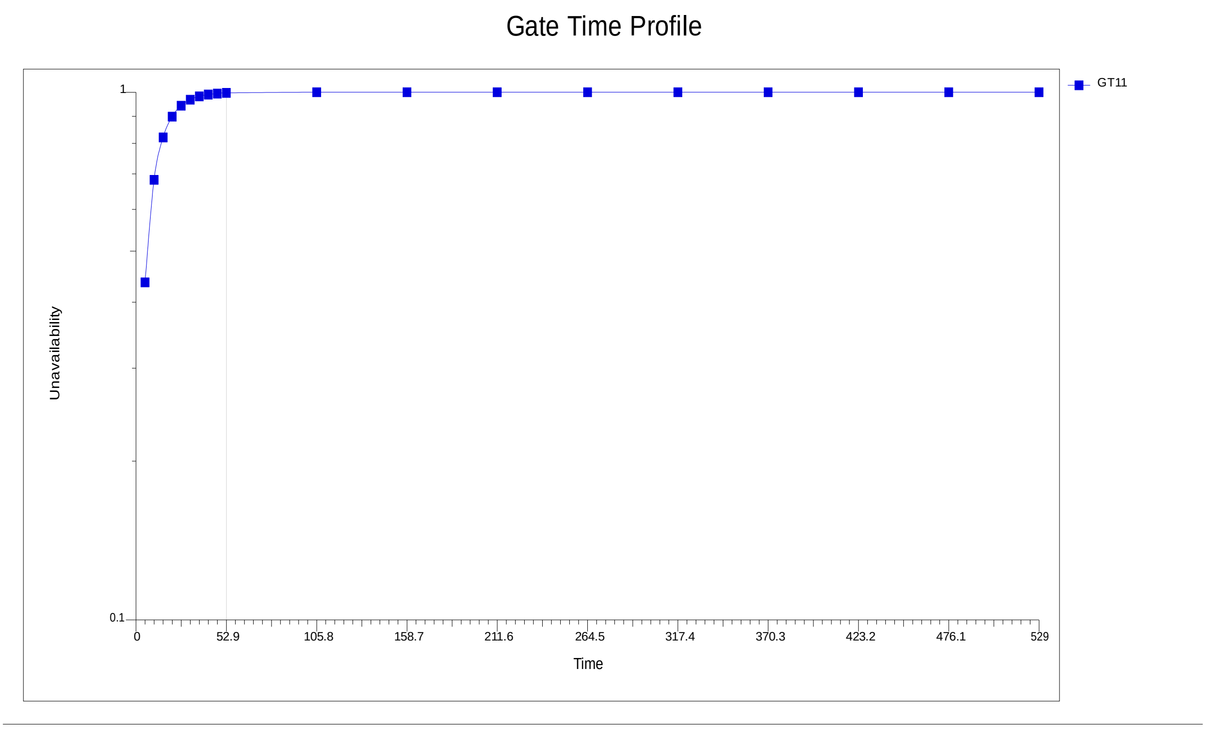


Figure 5.39 Gate time profile of un-availability of E2-LHD2

- **Fussel-Vessely Importance graphs of study area-1:**

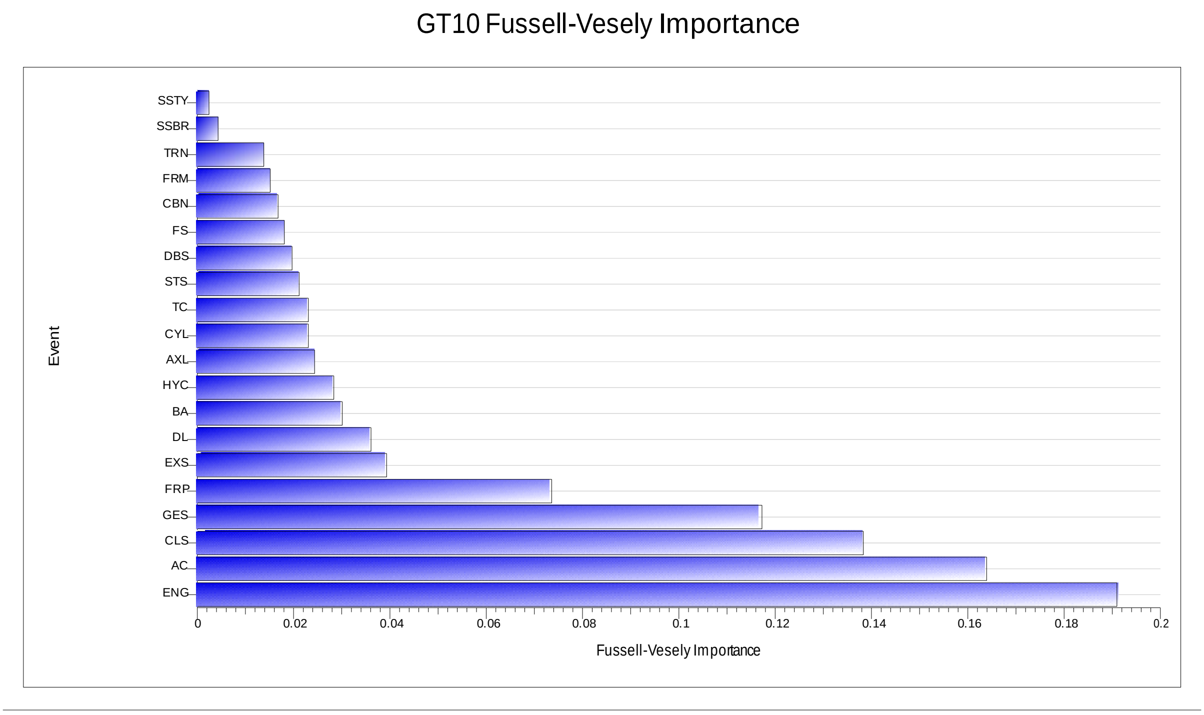


Figure 5.41 End gate Fussell-Vesely Importance plot of LH22

- **Fussel-Vessely Importance graphs of study area-2:**

GT11 Fussell-Vesely Importance

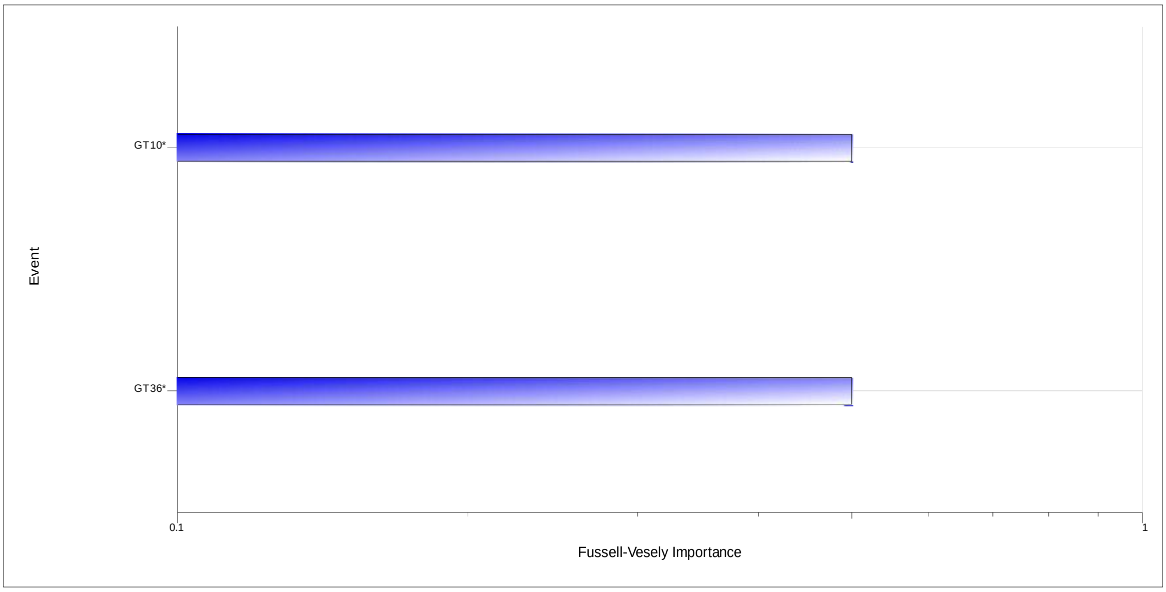


Figure 5.42 End gate Fussell-Vesely Importance plot of LHD1

GT11 Fussell-Vesely Importance

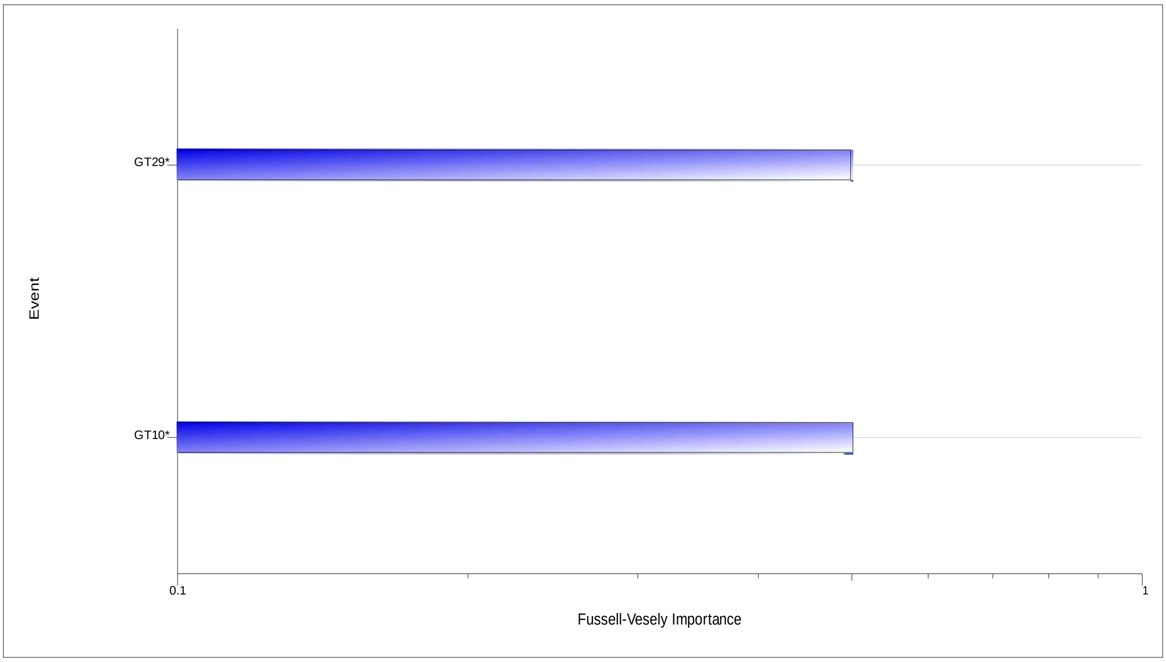


Figure 5.43 End gate Fussell-Vesely Importance plot of LHD2

- **Fussel-Vessely Importance graphs of study area-3:**

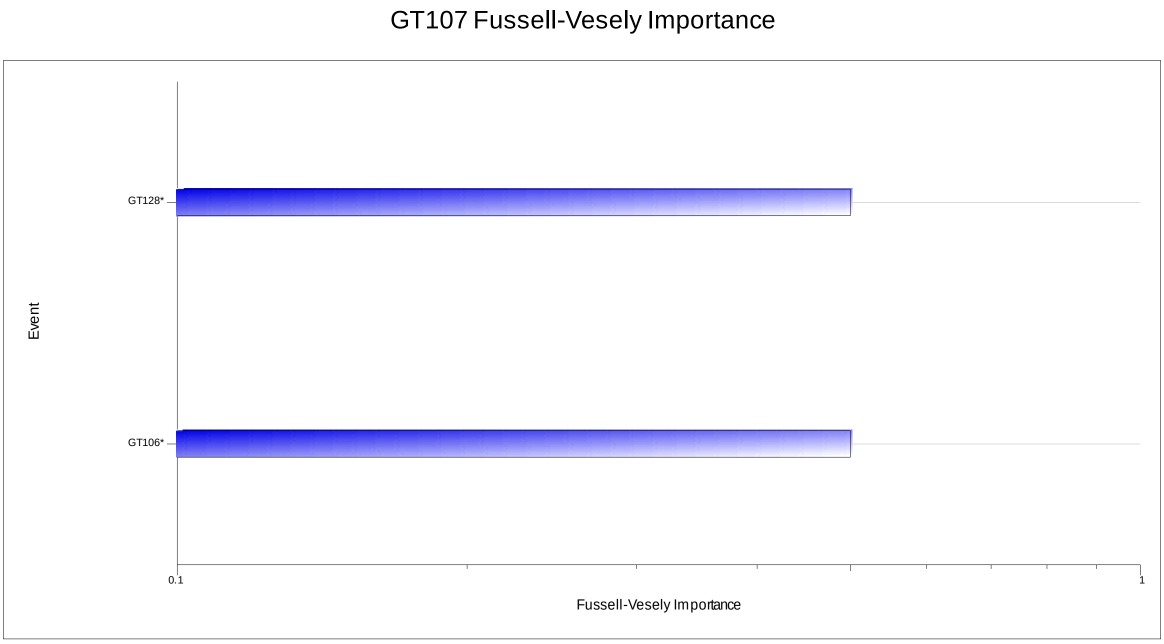


Figure 5.44 End gate Fussell-Vesely Importance plot of E1-LHD1

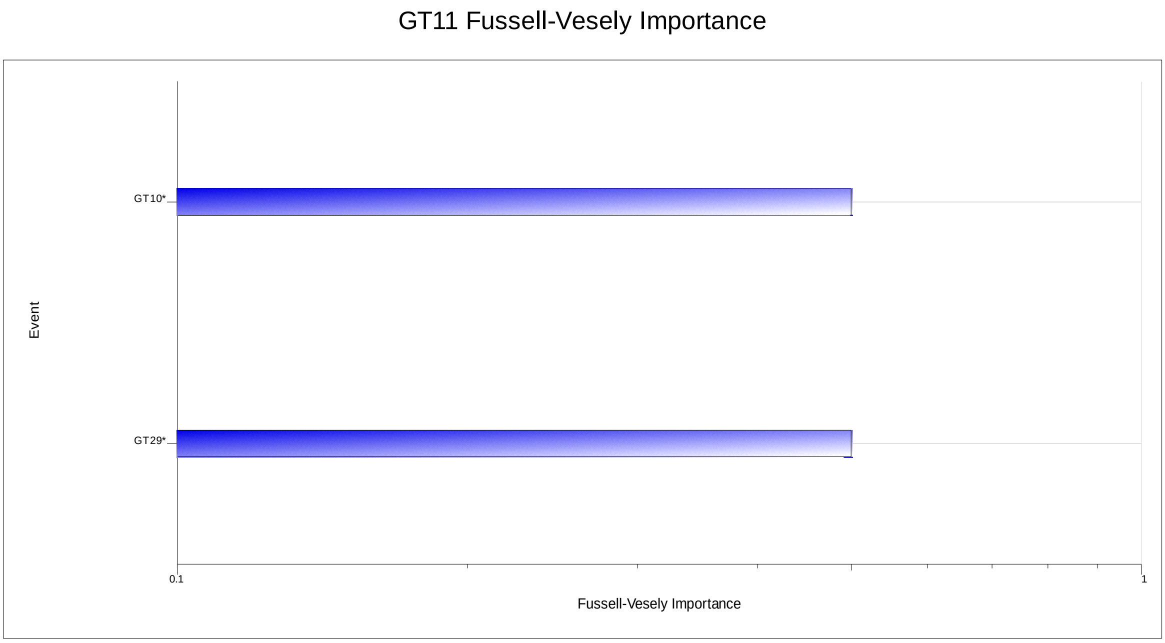


Figure 5.45 End gate Fussell-Vesely Importance plot of E2-LHD2

- **Results summary screenshot of study area-2:**

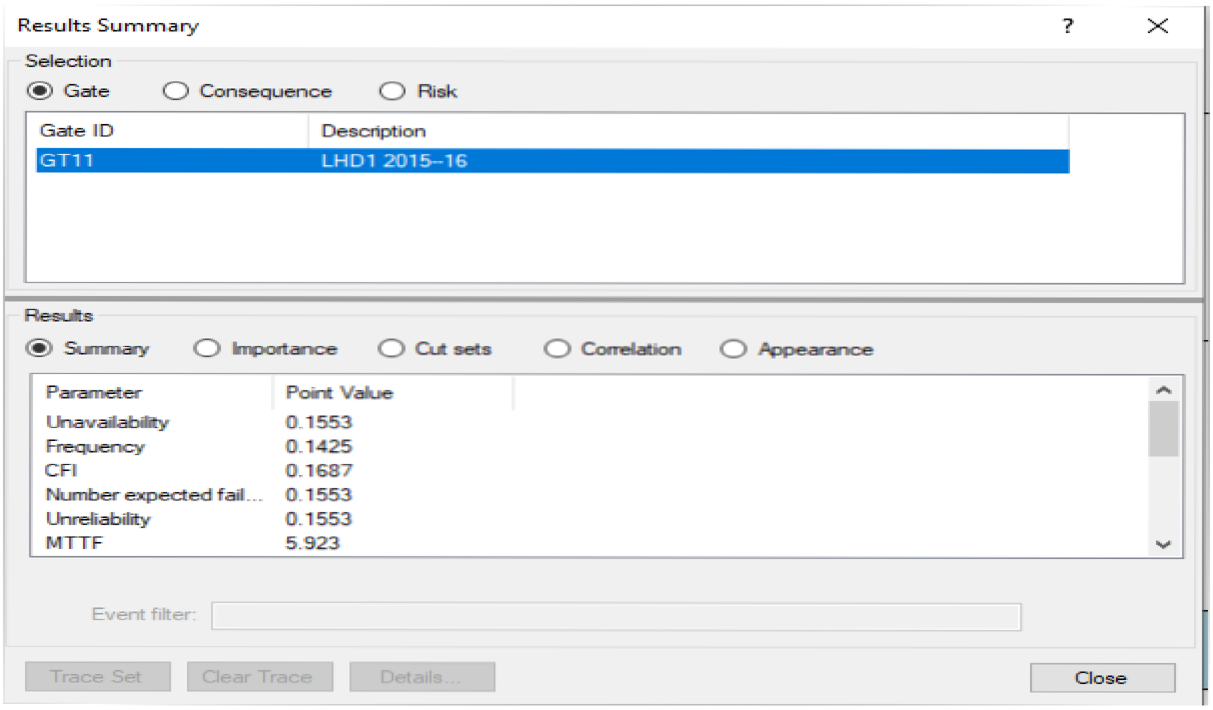


Figure 5.47 An example of results summary of LHD1

- **Results summary screenshot of study area-3:**

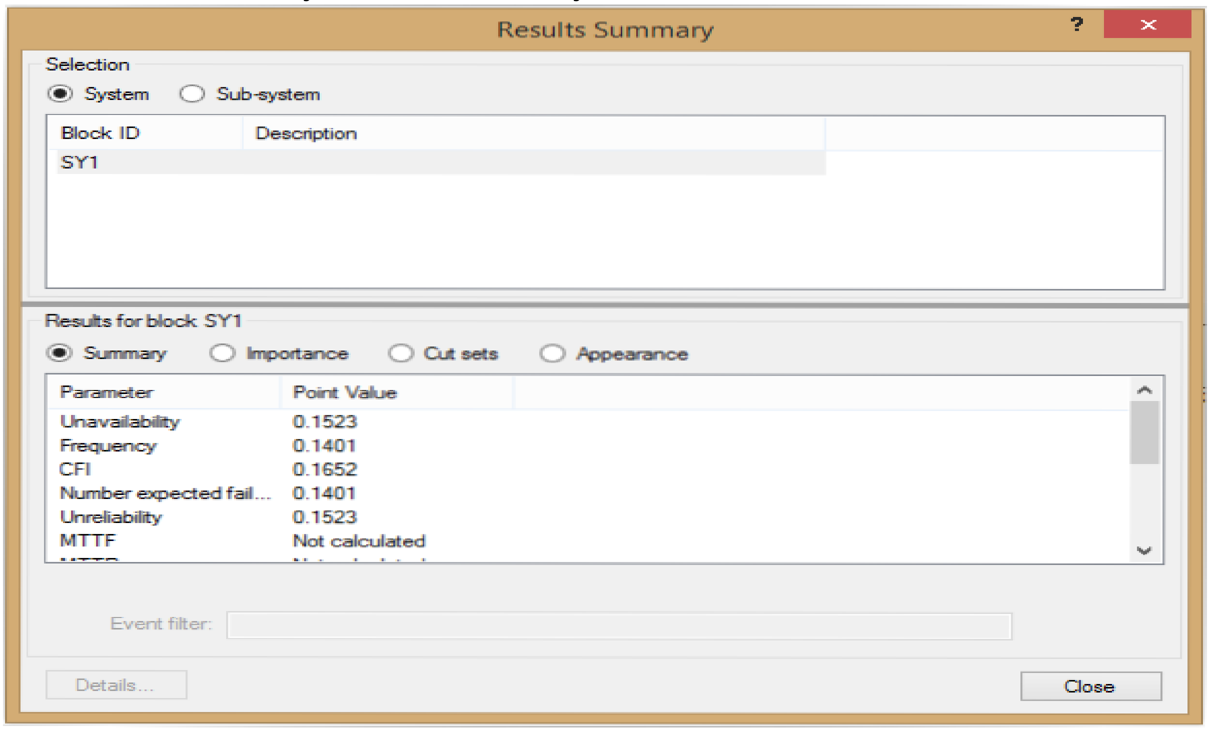


Figure 5.48 An example of results summery screenshot of E1-LHD1

Table 5.14 FMEA work sheet (process FMEA) of LHDs of study area-2

Component Description	Potential Failure Mode	Effects Description	Potential Cause (s)	Risk Index				Recommended Actions	Actions taken	Action results			
				S	**O**	**D**	**RPN**			**S**	**O**	**D**	**RP N**
Sub-system of Engine (SSE)	Cylinder liners broken down (F1)	System in-operable to perform the intended task	Due to insufficient lubrication , and wear, and tear	8	6	3	144	Replace the cylinder liner with new one, and provide sufficient lubrication for the engine parts	Replacement action of the engine parts should helps to machine operable	6	4	3	72
	Exhaust manifold gasket problem (F2)	Performance issues such as decrease in power, accelerator and fuel efficiency	Engine wiring and heat from the exhaust gases	8	3	4	96	Fit the new gasket by pushing it into the cylinder head	Replacement action should improve the performance of the engine	5	3	4	60
	Not functioning of engine cooling system (F3)	Engine will get overheat, squeezes immediately	Lack of repair action, and insufficient cooling medium	7	4	6	168	Clean the cooling system frequently, and provide sufficient of cooling medium	Provision of cooling medium will helps the engine to operate	4	5	4	80

	Fuel top up damage (F4)	Decrease the fuel efficiency	A faulty pump with low pressure	7	3	7	147	Replacement of the fuel pump with a new one	Improves the performance of the machine	5	3	7	105
Sub-system Electrical System (SSEl)	Starting problem (F5)	Machine won't start	Starter broken, Bad ignition system	9	3	5	135	Replacement of modified starter and ignition plug	Replacement of parts should operates the machine	5	3	5	75
	Water insert in the electrical panel (F6)	Damage of wires and short circuit	Wires can mold or corrosion	6	4	6	144	Replace the wires and protect with necessary provisions	Replacement action should operates the machine	3	4	6	72
	Electronic monitoring system (F7)	Unable to control the machine operation	Due to loose connections of wiring	9	4	5	180	Poor connections should be tightened in repair action	Repair action should helps to control the operation of the vehicle	6	3	5	90
	Fire protection system (F8)	Creates accidents prone area	Fire sprinkler system being shut off before the fire starts	9	3	6	162	Keep all fires, and heaters well guarded, especially open fires	Provided provisions will helps to reduce the accidents	5	3	7	105

Sub-system of Body (SSBo)	Door glass sliding problem (F9)	Bind at the corners	Adjusting screw fully tightened	7	6	2	84	Provide proper alignment between glass and frame	Alignment action reduces the sliding problem	4	6	2	48
	Door glass came out (F10)	Operator gets affected by the environmental issues	Mis-adjustment between glass and frame	6	4	2	48	Adjust the glass with roller adjustment screw	Adjustment action improves the alignment	4	4	2	32
	Rear wiper motor connection failure (F11)	Hard functioning of the wiper blades	Noisy in operation and stuck in operation	8	5	2	80	Replacement of new wiper set up	Replacement action provides the smooth operation	6	3	2	36
	Front light frame mounting broken (F12)	Impacts on vehicle operation, driver visibility	Vibration due to harsh working environment	9	7	2	126	Replacement of light frame mounting	Replacement action should provides the machine operable	6	7	2	84
	Rare axle stud broken (F13)	Un even wear on the tyre	Aging factor of the stud	8	5	3	120	Replace with a new stud for the axle	Replacement action helps to machine operable	5	4	3	60

Sub-system of Brake (SSBr)	Parking problem (F14)	Traffic congestion causes to brake failure	Lack of sufficient parking at event site	7	6	3	126	Recommended actions suggest to the operator	Skill of the operator should improves the brake life	5	6	3	90
	Brake oil leakage (F15)	Serious safety concerns	Fluid level in the reservoir is low	9	5	3	135	Maintain the fluid level by proper arrangements	Repair actions could control the oil leakage	7	5	3	105
	Auto park braking (F16)	It creates problematic situation when vehicle is parking on a slope	Loss of fluid pressure in the braking system and due to hose cracks or breaks	8	6	3	144	Provide the sufficient fluid pressure and initiate the repair action immediately	Repair action should helps to control the problematic situation	6	4	3	72
	Brake pedal broken (F17)	Not possible to control the vehicle's operation	Due to rust formation on the brake pedal	9	5	4	180	Replace the brake pedal with one	Replacement action should helps to control the vehicle's operation	6	4	4	96
Sub-system of Transmission	Gear shifting problem (F18)	Overall damage of the transmission system	A clutch that fails to dis-engage from the fly wheel	8	5	4	160	Replacement of the clutch plates with a new one	Replacement action should reduce the gear shifting problem	6	5	4	120

(SSTr)	Articulation problem (F19)	Slurring of speech, hearing loss	Difficulties in articulating sounds	9	6	3	162	Recommend suggestions to the operator about machine operation	Skill of the operator should minimize the problem	7	6	3	126
	Torque converter lock up problem (F20)	Won't be able to transfer the power from engine to the transmission system	Strange noise, higher stall speeds and slipping of gears	8	4	4	128	Repair the lock up problem	Repair action should reduce the problem	6	4	4	96
	Drive shaft belt broken (F21)	Stops working of the machine	Belt breaks, slips and wear out	9	5	3	135	Replace with a new belt	Replacement action helps to machine operable	7	5	3	105
Sub-system of Hydraulics (SSH)	Cylinder damage (F22)	Cracks on the cylinder cover	Improper lubrication and wear and tear	9	6	3	162	Provide sufficient lubrication	Proper lubrication system increase the cylinder life	6	4	4	96
	Hydraulic pump failure (F23)	Failure chain reaction in the system	Poor system design and low contamination control	6	6	4	144	Replacement of a pump with modified design	Replacement action contribute to control the failures	4	3	5	60

	Fuel air lock (F24)	Complete stoppage of fuel flow	Air leaking into the fuel delivery line	7	4	5	140	Eliminated by turning the engine over for a time using the starter motor	Replacement of modern diesel injection systems reduce the air locking	5	4	4	80
	Fuel top up damage (F25)	Decrease the fuel efficiency	A faulty pump with low pressure	7	3	7	147	Replacement of the fuel pump with a new one	Improves the performance of the machine	5	3	7	105
Sub-system of Tyre (SSTy)	Wheel stud broken (F26)	Wheel and tyre to separate them from vehicle	Over-torquing and under-torquing the lug nuts	9	5	3	135	Recommend suggestion to the maintenance personnel	Recommended suggestions should improves the stud life	7	5	3	105
	Tyre puncture (F27)	Machine stopped for repair	Poor under foot condition and improper inflation	9	4	4	144	Remove and send to maintenance work place	Maintenance action helps to machine operable	7	4	4	112
	Tyre nozzle lock (F28)	Cover for the tyre valve brakeage	Harsh road condition	8	5	4	160	Replace with a new cover plate	Replacement action helps to machine runs smooth	6	6	3	108

Sub-system of Mechanical (SSM)	Dump box welding work (F29)	Production stoppages	Poor welding at the joints	8	5	2	80	To be weld at the required portions	Repaired portions continuous the production	6	5	2	60
	Bucket attachment system (F30)	Production stoppages	Broken due to poor design, week strength and overload	9	5	3	135	Replace with a modified design and strengthened one	Replacement action should continuous the work	7	5	3	105
	Front axle replacement (F31)	Hard operation of equipment	Overloading, Lifting cylinder brakeage	8	6	3	144	Replace the cylinder breakage with a modified design	Replacement of the component improves the operation	5	6	3	90
	Boom functioning slow (F32)	Reduce the production levels	Feed assembly damage	9	5	3	135	Remove and replace the feed assembly	Replacement action improves the production levels	6	5	3	90
	Lift arm broken (F33)	Boom attachment can not possible to lift the bucket	Due to improper lubrication between the parts	8	6	3	144	Replace the lift arm with one	Replacement action can lift the lift assembly	7	4	2	56

Table 5.17 Estimated values of risk indexed parameters and RPN metrics of study area-2

Sub-system	Failure Type	Risk Indexed Parameters			RPN	Action Results of risk Indexed Parameters			Action Results of RPN
		(S)	**(O)**	**(D)**		**(S)**	**(O)**	**(D)**	
SSE	F1	8	6	3	144	6	4	3	72
	F2	8	3	4	96	5	3	4	80
	F3	7	4	6	168	4	5	4	80
	F4	7	3	7	147	5	3	7	105
SSEl	F5	9	3	5	135	5	3	5	75
	F6	6	4	6	144	3	4	6	72
	F7	9	4	5	180	6	3	5	90
	F8	9	3	6	162	5	3	7	105
SSBo	F9	7	6	2	84	4	6	2	48
	F10	6	4	2	48	4	4	2	32
	F11	8	5	2	80	6	3	2	36
	F12	9	7	2	126	6	7	2	84
	F13	8	5	3	120	5	4	3	60
SSBr	F14	7	6	3	126	5	6	3	90
	F15	9	5	3	135	7	5	3	105
	F16	8	6	3	144	6	4	3	72
	F17	9	5	4	180	6	4	4	96
SSTr	F18	8	5	4	160	6	5	4	120
	F19	9	6	3	162	7	6	3	126
	F20	8	4	4	128	6	4	4	96
	F21	9	5	3	135	7	5	3	105
SSH	F22	9	6	3	162	6	4	4	96
	F23	6	6	4	144	4	3	5	60
	F24	7	4	5	140	5	4	4	80
	F25	7	3	7	147	5	3	7	105
SSTy	F26	9	5	3	135	7	5	3	105
	F27	9	4	4	144	7	4	4	112
	F28	8	5	4	160	6	6	3	108
SSM	F29	8	5	2	80	6	5	2	60
	F30	9	5	3	135	7	5	3	105
	F31	8	6	3	144	5	6	3	90
	F32	9	5	3	135	6	5	3	90
	F33	8	6	3	144	7	4	2	56

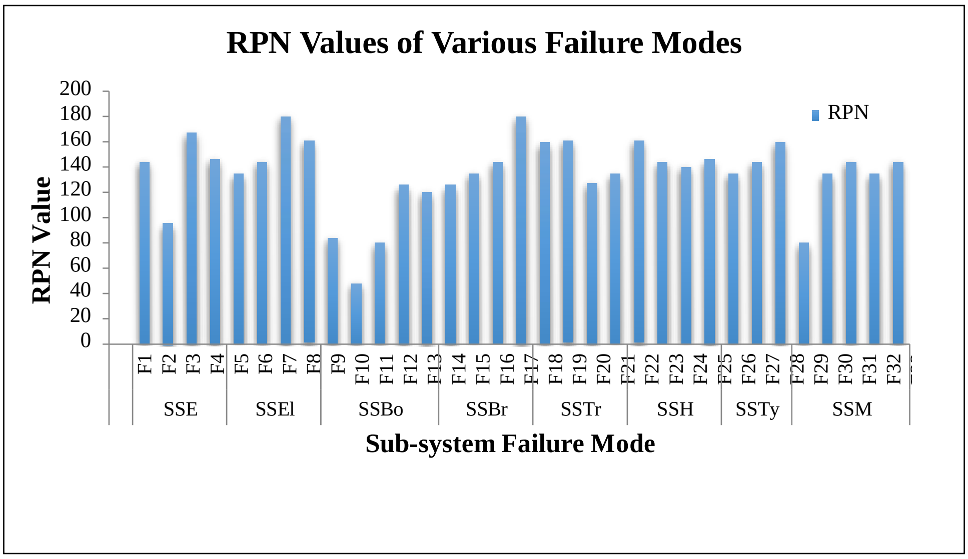


Figure 5.53 (a) RPN values of various failure modes of study area-2

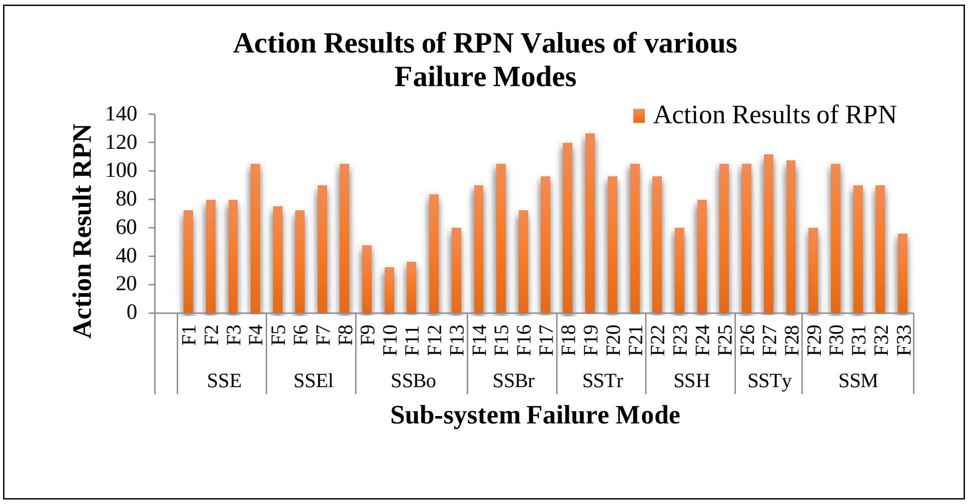


Figure 5.53 (b) Action results RPN values of various failure modes of study area-2

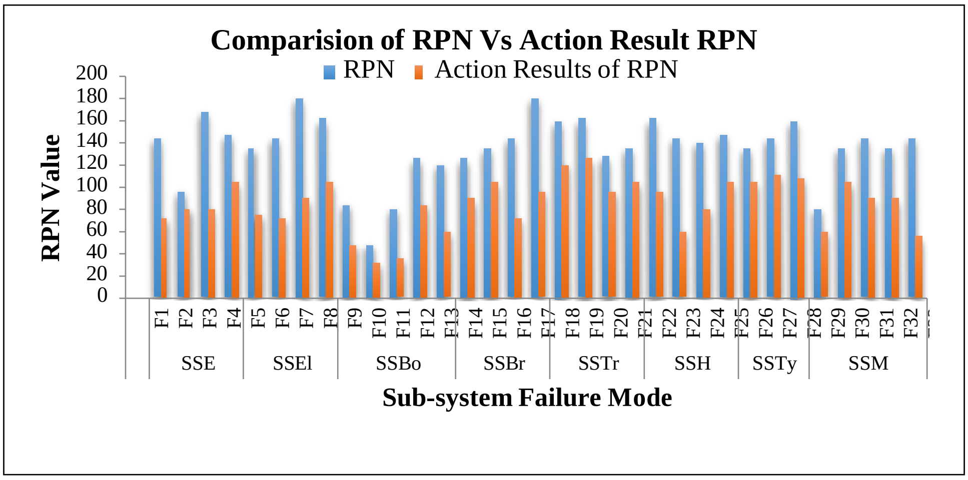


Figure 5.56 Percentage variation of RPN with action result RPN of study area-2

Table 5.15 FMEA work sheet (process FMEA) of LHDs of study area-3

Sub-system	Potential Failure Mode	Effects Description	Potential Cause (s)	Risk Index				Recommended Actions	Actions taken	Action results			
				S	**O**	**D**	**RPN**			**S**	**O**	**D**	**RP N**
SSE	Accelerator pedal stuck (F1)	Dangerous to the operator and the opposite person	A dirty air in the throttle body and cable in the air intake system	9	4	5	180	Cleaning the throttle body	Repair action should release this symptom	5	2	6	60
	Exhaust manifold gasket problem (F2)	Performance issues such as decrease in power, accelerator and fuel efficiency	Engine wiring and heat from the exhaust gases	8	3	4	96	Fit the new gasket by pushing it into the cylinder head	Replacement action should improve the performance of the engine	5	3	4	60
	Over heating problem (F3)	Radiator damage	A small leak or evaporation of coolant oil	7	6	3	126	Repairing of leak and provide coolant oil	Repairing of the parts will control the leakage	5	6	2	60
	Fan belt and pulley problem (F4)	Catastrophic engine damage	Misalignment forces the belt to kink or twist	8	6	3	144	Provide premature wear resistant and proper alignment	Repair action should reduces the fan belt breakages	5	6	3	90

	Fuel air lock (F5)	Complete stoppage of fuel flow	Air leaking into the fuel delivery line	9	6	3	162	Eliminated by turning the engine over for a time using the starter motor	Replacement of modern diesel injection systems reduce the air locking	6	5	3	90
	Fuel top up damage (F6)	Decrease the fuel efficiency	A faulty pump with low pressure	7	3	4	84	Replacement of the fuel pump with a new one	Improves the performance of the machine	5	3	4	60
SSEl	Starting problem (F7)	Machine won’t start	Starter broken, Bad ignition system	9	3	5	135	Replacement of modified starter and ignition plug	Replacement of parts operates the machine	5	3	5	75
	Water insert in the electrical panel (F8)	Damage of wires and short circuit	Wires can mold or corrosion	6	4	6	144	Replace the wires and protect with necessary provisions	Replacement action should operates the machine	3	4	6	72
SSBo	Door glass sliding problem (F9)	Bind at the corners	Adjusting screw fully tightened	3	6	2	36	Provide proper alignment between glass and frame	Alignment action reduces the sliding problem	2	6	2	24

	Door glass came out (F10)	Operator gets affected by the environmental issues	Mis-adjustment between glass and frame	7	5	2	70	Adjust the glass with roller adjustment screw	Adjustment action improves the alignment	5	4	2	40
	Rear wiper motor connection failure (F11)	Hard functioning of the wiper blades	Noisy in operation and stuck in operation	6	3	2	36	Replacement of new wiper set up	Replacement action provides the smooth operation	4	3	2	24
	Front axle stud has broken (F12)	Uneven wear on the tyre	The aging factor of the stud	8	7	2	112	Replace with a new stud for the axle	Replacement action helps to machine operable	6	6	2	72
SSBr	Parking problem (F13)	Traffic congestion causes to brake failure	Lack of sufficient parking at the event site	7	6	2	84	Recommended actions suggest to the operator	The skill of the operator improve the brake life	5	5	3	75
	Brake oil leakage (F14)	Serious safety concerns	The fluid level in the reservoir is low	9	5	3	135	Maintain the fluid level by proper arrangements	Repair actions could control the oil leakage	7	5	3	105
SSTr	Torque converter lock-up problem (F15)	Won’t be able to transfer the power from the engine to	A strange noise, higher stall speeds and slipping of gears	8	4	4	128	Repair the lock-up problem	Repair action should reduce the problem	6	4	4	96

		the transmission system											
	Driveshaft belt broke (F16)	Stops working of the machine	Belt breaks, slips and wear out	9	5	3	135	Replace with a new belt	Replacement action should help to machine operable	7	5	3	105
	Gear shifting problem (F17)	Overall damage to the transmission system	A clutch that fails to disengage from the flywheel	8	5	4	160	Replacement of the clutch plates with a new one	Replacement action should reduce the gear shifting problem	6	5	3	90
	Articulation problem (F18)	Slurring of speech, hearing loss	Difficulties in articulating sounds	9	6	3	162	Recommend suggestions to the operator about operation	The skill of the operator should minimize the problem	7	6	3	126
SSH	Cylinder damage (F19)	Cracks on the cylinder cover	Improper lubrication and wear and tear	7	4	5	140	Provide sufficient lubrication	Proper lubrication system increase the cylinder life	5	4	5	100
	Hydraulic pump failure (F20)	The failure chain reaction in the system	Poor system design and low contamination control	6	5	4	120	Replacement of a pump with a modified design	Replacement action should contribute to control the	5	4	4	80

									failures				
	Charge air cooler hose open (F21)	Damage the intercooler parts	Drop in the pressure of the compressed air	5	5	4	100	Replace the new intercooler parts	Replacement action controls the damages	3	5	4	60
	Coolant leakage (F22)	Hoses get hard and brittle	Coolant join with water pump, radiator and heater core	7	4	6	168	Recommend provisions to hose get smooth	Repair action reduces the hose problems	4	4	6	96
	Hydraulic oil leakage (F23)	Machine stoppages and component failures	Contaminated lubricants	5	3	7	105	Replace the hydraulic actuating valve	Replacement action control the stoppages	3	3	6	54
SSTy	Wheel stud has broken (F 24)	Wheel and tyre to separate them from vehicle	Over-torquing and under-torquing the lug nuts	9	5	3	135	Recommend suggestion to the maintenance personnel	Recommended suggestions should improve the stud life	7	5	3	105
	Tyre puncture (F25)	The machine stopped for repair	Poor underfoot condition and improper inflation	9	4	4	144	Send to the maintenance workplace	Maintenance action helps to machine operable	7	4	4	112
	Tyre nozzle lock (F26)	Cover for the tyre valve breakage	Harsh road condition	8	5	3	120	Replace with a new cover plate	Replacement action should help to machine runs smooth	6	5	3	90

SSM	Dump box welding work (F27)	Production stoppages	Poor welding at the joints	8	5	2	80	To be weld at the required portions	Repaired portions should continuous the production	6	5	2	60
	Bucket attachment system (F28)	Production stoppages	Broken due to poor design, week strength, and overload	9	6	3	162	Replace with a modified design and strengthened one	Replacement action should continue the work	7	6	3	126
	Front axle replacement (F29)	Hard operation of equipment	Overloading, Lifting cylinder breakage	9	5	3	135	Replace the cylinder breakage with a modified design	Replacement of the component improves the operation	6	6	3	108
	Boom broken (F30)	Production stoppages	Overloading, Lifting cylinder breakage and poor welding at the joints	9	6	2	108	Remove and replace with a strengthened one	Replacement action should continuous the production	7	4	3	84

Table 5.18 Estimated values of risk indexed parameters and RPN metrics of study area-3

Sub-system	Failure Type	Risk Indexed Parameters			RPN	Action Results of Risk Indexed Parameters			Action Results of RPN
		(S)	(O)	(D)		(S)	(O)	(D)	
SSE	F1	9	4	5	180	5	2	6	60
	F2	8	3	4	96	5	3	4	60
	F3	7	6	3	126	5	6	2	60
	F4	8	6	3	144	5	6	3	90
	F5	9	6	3	162	6	5	3	90
	F6	7	3	4	84	5	3	4	60
SSEl	F7	9	3	5	135	5	3	5	75
	F8	6	4	6	144	3	4	6	72
	F9	3	6	2	36	2	6	2	24
	F10	7	5	2	70	5	4	2	40
	F11	6	3	2	36	4	3	2	24
	F12	8	7	2	112	6	6	2	72
SSBr	F13	7	6	2	84	5	5	3	75
	F14	9	5	3	135	7	5	3	105
SSTr	F15	8	4	4	128	6	4	4	96
	F16	9	5	3	135	7	5	3	105
	F17	8	5	4	160	6	5	3	90
	F18	9	6	3	162	7	6	3	126
SSH	F19	7	4	5	140	5	4	5	100
	F20	6	5	4	120	5	4	4	80
	F21	5	5	4	100	3	5	4	60
	F22	7	4	6	168	4	4	6	96
	F23	5	3	7	105	3	3	6	54
SSTy	F24	9	5	3	135	7	5	3	105
	F25	9	4	4	144	7	4	4	112
	F26	8	5	3	120	6	5	3	90
SSM	F27	8	5	2	80	6	5	2	60
	F28	9	6	3	162	7	6	3	126
	F29	9	5	3	135	6	6	3	108
	F30	9	6	2	108	7	4	3	84

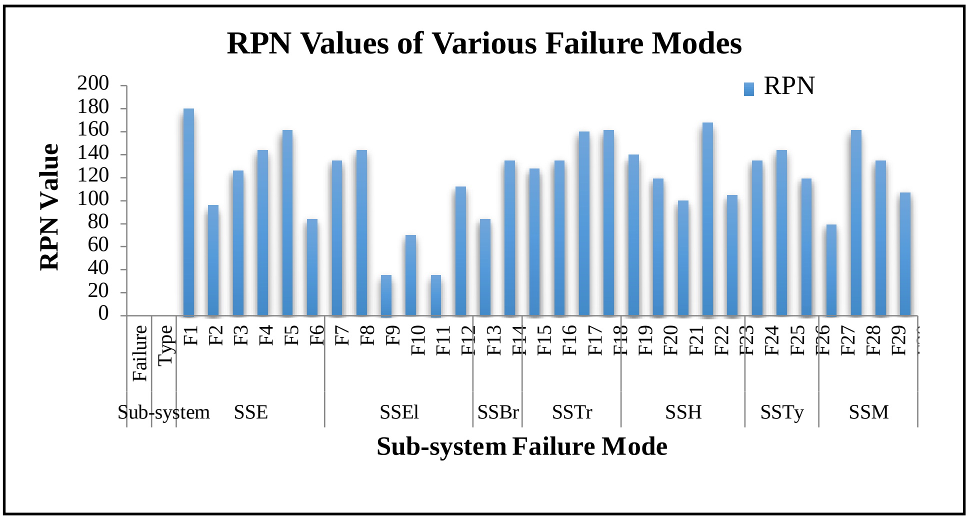


Figure 5.54 (a) RPN values of various failure modes of study area-3

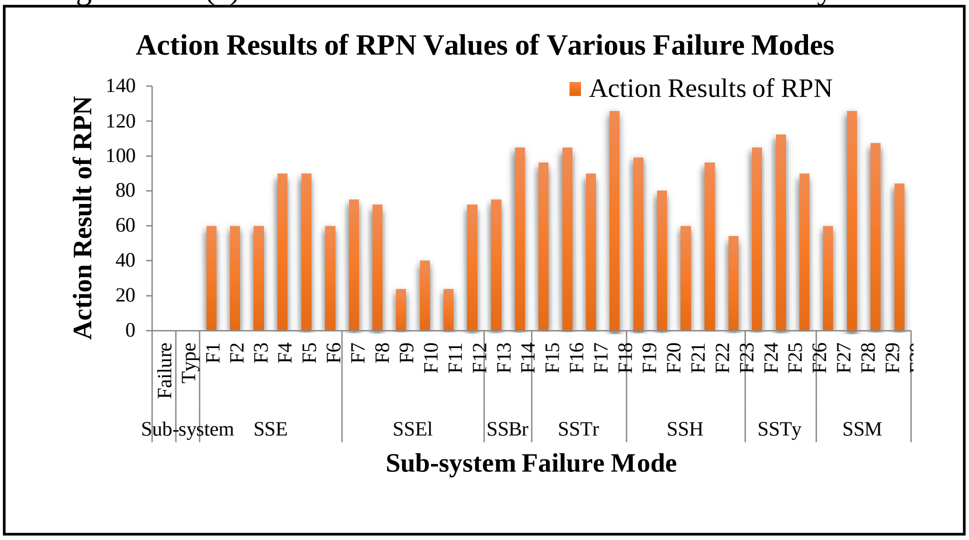


Figure 5.54 (b) Action result RPN values of various failure modes of study area-3

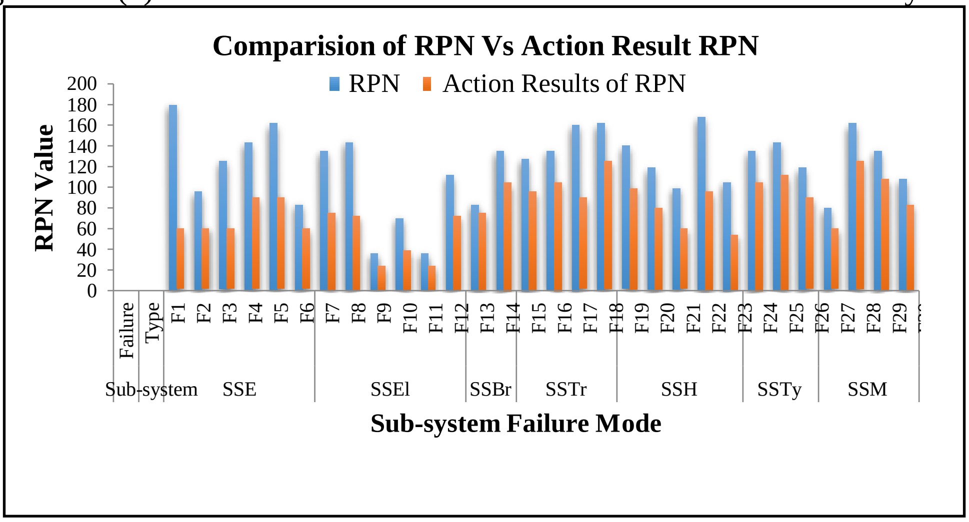


Figure 5.57 Percentage variation of RPN with action result RPN of study area-3

APPENDIX-3

Table 7.3 Classified data of machinery of study area-2 for OEE analysis

Machine	SShr	SMhr	SAhr	BDhr	MAhr	IDhr	MWhr
LHD-1	17856	399	17458	661	16797	1519	15278
LHD-2	17856	235	17621	678	16943	1804	15139
LHD-3	17856	192	17664	24	17420	3720	13700
LHD-4	17856	178	17679	844	16835	1488	15347
LHD-5	17856	243	17613	342	17271	1386	15885

Table 7.4 Computed and compared values of OEE of study area-2

Machine	Computed OEE				% Variation
	% Avl	%PR	%QR	%OEE	
LHD-1	94.07	85.55	96.21	76.70	8.30
LHD-2	94.89	84.78	96.15	77.35	7.65
LHD-3	97.56	77.95	99.86	75.94	9.06
LHD-4	94.28	85.94	95.22	77.15	7.85
LHD-5	96.72	88.96	98.05	84.36	0.64

Table 7.5 Classified data of machinery of study area-3 for OEE analysis

Machine	SShr	SMhr	SAhr	BDhr	MAhr	IDhr	MWhr
E1-LHD1	14232	542	13690	3036	10654	6271	4383
E2-LHD2	11556	354	11202	3309	7893	3847	4046
E3-LHD3	13680	570	13110	1370	11740	5859	5881
E5-LHD5	14328	597	13731	1139	12592	6201	6391
E6-LHD6	13680	570	13110	1479	11631	5341	6290

Table 7.6 Computed and compared values of OEE of study area-3

Machine	Computed OEE				% Variation
	% Avl	%PR	%QR	%OEE	
E1-LHD1	74.86	62.11	87.82	40.83	44.17
E2-LHD2	68.30	65.01	80.46	35.72	49.28
E3-LHD3	85.82	72.98	99.54	62.34	22.66
E5-LHD5	87.88	74.60	91.70	60.11	24.89
E6-LHD6	85.02	75.97	98.71	63.75	21.25

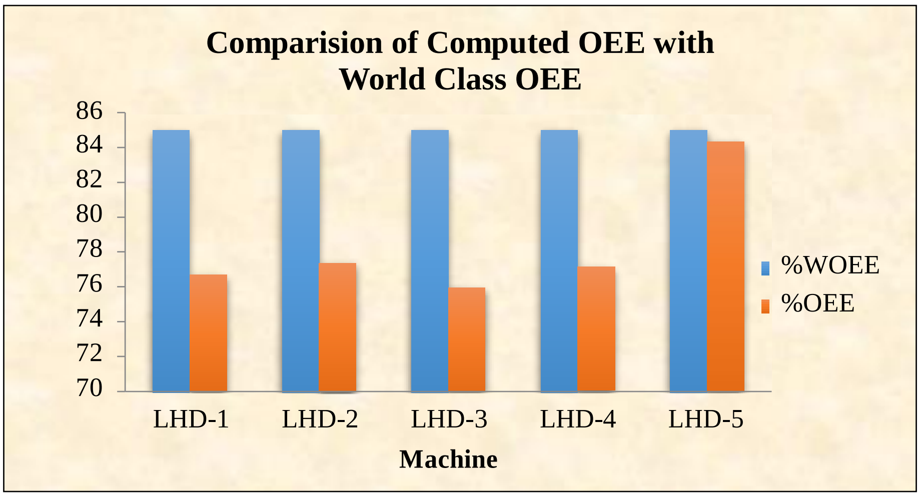


Figure 7.3 Comparison chart of OEE of study area-2

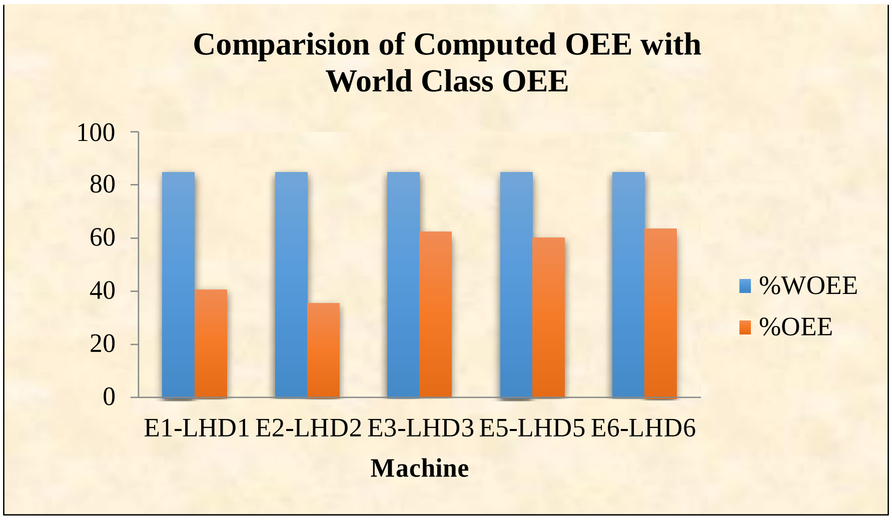


Figure 7.4 Comparison chart of OEE of study area-3

BIO-DATA

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Course	**Specialization**	**University /Board**	**Percentage /Grades**	**Year of Completion**
Ph.D	Investigations on Performance of Load-Haul-Dumpers and Improvement of its Availability and Utilization using Reliability Analysis	National Institute of Technology Karnataka **(N.I.T.K)**	9.5/10 (CGPA)	2021
M. Tech	Machine Design	**J.N.T.U.K**	78.00 %	2012
B. Tech	Mechanical Engineering	**J.N.T.U.K**	68.00 %	2009
Intermediate	M.P.C	Board of Intermediate Education**, A.P.**	72.00 %	2005
SSC	State Govt. Syllabus	Board of Secondary Education**, A.P.**	72.00 %	2003

Professional Experiences:

Period	Designation	Organization/Institution	No. of Years/Months
10/10/2009 - 30/10/2010	**Design Engineer (Quality Assurance)**	ACMI (Aluminium Components Manufacturing Industries)-Jeedimetla-III, Hyderabad	01 Yr
17/10/2012 - 05/07/2014	**Assistant professor**	Gudlavalleru Engineering College, Krishna D.t, Vijayawada-Andhra Pradesh	01 Yr & 09 Months
04/08/2014 - 20/12/2015	**Assistant professor**	Bharat Institute of Engineering & Technology, Rangareddy D.t, Hyderabad-Telangana	01 Yr & 04 Months
31/12/2015 - 11/02/2021	**Research Scholar/ Teaching Assistant**	National Institute of Technology Karnataka (NITK), Surathkal, Mangalore, INDIA	05 Yrs & 02 Months
Total Work Experience			**09 Yrs & 03 Months**

Publications:

Total Number of Publications:23 (SCOPUS/SCI/Web of Science:10 and Others:13)

	Score	Citation	H-Index
Research Gate	9.73	49	04
Scopus	---	49	04
Google Scholar	---	49	04

Journal Publications: 17

- **J. Balaaju. (2012)**. “Prediction of Surface Finish by End Milling using Factorial Technique.” *Int. J of Mech. Sciences, Tech. and Humanities*, 59, 647-653.
- **J. Balaaju. (2013)**. “Effect And Optimization Of Machining Parameters On Cutting Force And Surface Finish In Turning Of Mild Steel And Aluminium.” *International Journal of Research in Engineering and Technology*, 2 (11).
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- **J. BalaRaju.,** M. Govinda.aj., and S. N. Murthy. Ch. **(2017)**. "Evaluation of influential measures to control the monetary aspects of load haul dump machine - case study", *J. of Mathematical Modelling of Engg. Problems*, 4 (4), 155-161.

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- **Balaraju. Jakkula.**, M. Govinda.aj., and Ch. S. N. Murthy. **(2017)**. "Performance of Load Haul Dumper in Underground Mines- An overview." *Int. Conf. on Deep Excavation, Energy Resources and Prod.*, **IIT, Kharagpur**, 24th-26th Jan'2017.

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