Availability Estimation and Management for Complex Processing Systems

By

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A thesis submitted to the School of Graduate Studies

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Faculty of Engineering and Applied Science

Memorial University of Newfoundland

May - 2016
St. John's, Newfoundland

Abstract

"Availability" is the terminology used in asset intensive industries such as petrochemical and hydrocarbons processing to describe the readiness of equipment, systems or plants to perform their designed functions. It is a measure to suggest a facility's capability of meeting targeted production in a safe working environment. Availability is also vital as it encompasses reliability and maintainability, allowing engineers to manage and operate facilities by focusing on one performance indicator. These benefits make availability a very demanding and highly desired area of interest and research for both industry and academia.

In this dissertation, new models, approaches and algorithms have been explored to estimate and manage the availability of complex hydrocarbon processing systems. The risk of equipment failure and its effect on availability is vital in the hydrocarbon industry, and is also explored in this research. The importance of availability encouraged companies to invest in this domain by putting efforts and resources to develop novel techniques for system availability enhancement. Most of the work in this area is focused on individual equipment compared to facility or system level availability assessment and management. This research is focused on developing an new systematic methods to estimate system availability. The main focus areas in this research are to address availability estimation and management through physical asset management, risk-based availability estimation strategies, availability and safety using a failure assessment framework, and availability enhancement using early equipment fault detection and maintenance scheduling optimization.

Keywords: Asset Management, Availability, Reliability, Maintainability, Safety, Risk Assessment, Root Cause Analysis, Fault Detection, Decision Trees, Maintenance Scheduling Optimization, Markov Decision Process, Genetic Algorithms

To my parents…

To my family, friends …

and

To my wife and kids…

Acknowledgments

All praises are due to almighty Allah, who has given us the opportunity and strength to complete this work. It is my pleasure to acknowledge several individuals for their guidance, contribution and support throughout my Ph.D. program.

First and foremost, I would like to offer my sincere thanks to my main supervisor, Dr. Faisal Khan, for all his support, guidance and encouragement throughout the program. Without his support and guidance, it would not have been possible to meet the research requirements of this Ph.D. work. I am also very thankful to my co-supervisors, Dr. Yan Zhang, Dr. Salim Ahmed and Dr. Syed A. Raza for their valuable guidance and support throughout this program.

I would like to offer thanks to my research colleagues Dr. Syed Asif Raza, Dr. Kamran Moghaddam and Dr. Fatai Adesina Anifowose for their contributions and support to develop some novel and outstanding solutions to address industry problems. I would like to extend sincere thanks to examination committee members, Dr. Ming Zuo, Dr. Syed Ahmed Imtiaz, and Dr. Long Fan for providing valuable feedback to improve the overall quality of the thesis. Along the way, several people have helped me in different ways to achieve my goal. I would to like to thank Mr. Khalid B. Hanif, Mr. Subba R. Ganti, Mr. Samith Rathnayaka and Dr. Refaul Ferdous for their help and support.

I am indebted to the graduate studies department of Memorial University for providing me with such a great opportunity. I am sincerely thankful to all who helped me, including the administrative, technical and academic staff at Memorial University.

Last but not least, I would like to thank my parents and family for their prayers and unselfish support in helping me to grow as a person and in securing for me an outstanding education. I take this opportunity to express my deep and heart-felt gratitude to my wife, Farida, for making great efforts to manage the family, which indeed enabled me to complete these studies. I also would like to express my thanks to my beloved children, Momena, Sarah, Ibrahim and Aamna for their understanding, patience and sacrifices during my studies.

Co-Authorship Statement

I, Qadeer Ahmed, hold a primary author status for all the Chapters in this dissertation. However, each manuscript is co-authored by my supervisor, co-researchers and colleagues, whose contributions have facilitated the development of this work as described below.

- **Qadeer Ahmed, Faisal I. Khan, Syed A. Raza, (2014) "A risk-based availability estimation using Markov method," International Journal of Quality & Reliability Management, Vol. 31 Issue: 2, pp.106-128.**

  Statement: I am the primary author and carried out most of the data collection, numerical modeling and analysis. I have drafted the manuscript and included all the comments after review from co-authors in the final manuscript. As co-author, Faisal I. Khan helped in developing the idea, reviewed, corrected the model and results. He also contributed in reviewing and revising the manuscript. As co-author, Syed A. Raza contributed through support in development of state dependent models along with reviewing and revising the manuscript.

- **Qadeer Ahmed, Faisal Khan, Salim Ahmed, (2014), "Improving safety and availability of complex systems using a risk-based failure assessment approach," Journal of Loss Prevention in the Process Industries, Volume 32, November 2014, pp. 218-229.**

Statement: In primary author capacity, I was involved in data collection and analysis, development of framework, implementation of framework for validation of the proposed framework and compilation of results. I have drafted the manuscript for review and comments, later, included all the comments from co-authors in the final manuscript. As co-author, Faisal I. Khan identified the improvements required for overall framework to be more practical and realistic. He supported in finalizing the methodology to implement the framework. He also contributed in reviewing and revising the manuscript. As co-author, Salim Ahmed contributed through support in development of case studies to validate the proposed framework along with reviewing and revising the manuscript.

- **Qadeer Ahmed, Kamran S. Moghaddam, Syed A. Raza, Faisal I. Khan, (2015), "A Multi Constrained Maintenance Scheduling Optimization Model for Hydrocarbon Processing Facilities," Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, pp 151-168**

  Statement: As a primary author, I was involved in development of the cost, reliability and availability optimization models. I carried out the data collection, analysis using the optimization code for all the optimization cases and formulation of results. I have drafted the manuscript for review and comments, later, included all the comments from co-authors in the final manuscript. As a co-author, Kamran S. Moghaddam contributed in coding the proposed optimization formulation and ensured its working in *optimization software, LINGO. He also contributed in reviewing and revising the manuscript. As co-author, Syed A. Raza supported in development of optimization formulation, especially development of failure model. Faisal I. Khan supported in developing the idea, reviewed, and provided comments to ensure models are representative of real plant conditions which includes maintenance cost, reliability and availability. He contributed in reviewing the draft manuscript and provided comments to improve the manuscript.*

- **Qadeer Ahmed, Fatai A. Anifowose, Faisal Khan, (2015), "System Availability Enhancement using Computational Intelligence based Decision Tree Predictive Model," Accepted - Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability**

  Statement: I am the primary author developed the concept of early fault detection to enhance system availability. I also carried out the data collection and analysis, development of fault detection schemes, designed experiments to include all the operating conditions. I have performed all the cases model execution using MATLAB and compilation of results. I have drafted the manuscript for review and comments, later, included all the comments from co-authors in the final manuscript. As a co-author, Fatai A. Anifowose participated in development the code and data stratification strategy in MATLAB using Decision Trees algorithms. He also contributed in reviewing and revising the manuscript. As co-author, Faisal Khan contributed in *developing the idea to detect machinery faults, reviewed, and feedback on the model and results. He also contributed in reviewing and suggesting areas to improve the manuscript.*

- **Abdel Kader Attou and Qadeer Ahmed, (2009), "Asset Management Practices at Qatargas," Proceedings of the 1st Annual Gas Processing Symposium, Doha, Qatar. Elsevier B.V.**

  Statement: I am the primary author in this paper and presented the importance of physical asset management in enhancing availability of assets. I have drafted the manuscript for review and comments, later, included all the comments from co-authors in the final manuscript. As a co-author, Abdel Kader Attou has contributed by reviewing the concept and its refinement. He suggested practical improvements based on his extensive experience in industry and supported the proposed asset management concept. He also reviewed the results and suggested changes in manuscript to enhance the quality of the paper.

Qadeer Ahmed

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List of Symbols & Abbreviations

Symbol/ Abbreviation	Description
A_{target}	Required Availability of a Complete System
CF_m	Cost of Corrective (failure) Task of Equipment, m
CI_m	Cost of Inspection of Equipment, m
CLF_m	Labor Cost/hour to Perform a Corrective Task for Equipment, m
CLI_m	Labor Cost/hour to Perform an Inspection Task for Equipment, m
CLM_m	Labor Cost/hour to Perform a Maintenance Task for Equipment, m
CLR_m	Labor Cost/hour to Perform a Replacement Task for Equipment, m
CM_m	Cost of Maintenance of Equipment, m
CMT_m	Cost of the Material of Equipment, m
CO_m	Cost of Operation Task of Equipment, m
CR_m	Cost of Replacement of Components in Equipment, m
$E[N_{mt}]$	Expected Number of Failures of Equipment, m, and Time, t
ERI_m	Equipment Risk Index of Equipment, m
R_{target}	Required Reliability of a Complete System
TF_m	Time Required to Perform a Corrective Repair for Equipment, m
TI_m	Time Required to Inspect Equipment, m
TM_m	Time Required to Perform Maintenance on Equipment, m

TR_m	Time Required to Replacement Equipment, m
α_m	Improvement Factor of Equipment, m
β_m	Shape Parameter of Equipment, m
λ_m	Scale Parameter of Equipment, m
ν_m	Rate of Occurrence of Failure (ROCOF)
ρ_m	Failure Cost Factor for Equipment, m
A	Availability
ACA	Asset Centric Approach
ALARP	As Low As Reasonably Possible
AM	Asset Management
AMMS	Asset Maintenance Management System
API	American Petroleum Institute
APMS	Asset Performance Management System
A_S	System Availability
As_R	Availability – System Rotating Equipment
Ass	Availability – System Static Equipment
A_U	Availability – Unit
DT	Decision Trees
FDC	Fault Detection and Control
FTA	Fault Tree Analysis
HP	High Pressure

ISO	International Standard Organization
ISO	International Standard Organization
L	Length of the Planning Horizon
LB	Lower Bound
LP	Low Pressure
M	Maintainability
M	Number of Equipment
M	Index for an Equipment, $\forall$ m $= \{1,2,3, \ldots, \mathrm{M}\}$
M’	Mean System Downtime
MTBF	Mean Time Between Failure
MDP	Markov Decision Process
MM	Markov Modeling
MTBF	Mean Time Between Failures
MTBM	Mean Time between Maintenance
RBD	Reliability Block Diagram
MTTR	Mean Time to Repair
OREDA	Offshore Reliability Data
PAM	Physical Asset Management
PERD	Process Equipment Reliability Database
PI	Priority Index
POF	Probability of Failure

QLRA	Qualitative Risk Assessment
QNRA	Quantitative Risk Assessment
R	Reliability
RA	Risk Assessment
RAM	Risk Assessment Matrix
RBAMM	Risk Based Availability Markov Model
RBD	Reliability Block Diagram
RI	Risk Index
ROA	Return on Investment
Rp	Reliability of Parallel System
Rs	Reliability of Series System
SHE	Safety, Health, and Environment
SR	System Rotating Equipment
SR_n	Subsystem in Rotating Equipment
SS	System Static Equipment
SS_n	Subsystem in Static Equipment
T	Number of Intervals over the Planning Horizon
T	Index for Time Period, $\forall\ t = \{1,2,3,\ldots,T\}$
TC	Total Cost
UB	Upper Bound
UKF	Unscented Kalman Filter

λ	Failure Rate
μ	Repair Rate

CHAPTER 1

INTRODUCTION AND OVERVIEW

1.1 Introduction

High availability means effective utilization and management of equipment, processes and other resources. This helps to improve the return on investment for all stakeholders by ensuring the facilities produce to meet required demand. Availability is a function of reliability and maintainability; therefore, availability is an important measure in the processing industry. Over the last decade, there has been an increasing trend of companies integrating processes and utilizing excess available capacities in other places to achieve economies of scale and improve plant availability. The overall availability management process requires many systems working concurrently to reap the real benefits. This requires multiple departments to work together such as Maintenance and Operations; and many systems to be aligned toward a common goal, along with continuous monitoring and improvement for sustainability.

There are many general methods to calculate the availability of systems and equipment. Different methods are used to estimate the availability of a product or a process.

Availability of processes has reliability and maintainability aspects embedded in the analysis, which makes it a powerful mechanism to manage businesses. Processing systems comprise different equipment with redundancies; for example, a liquefaction system converts gas into liquid by cooling and processing the gas through many compressors, turbines, vessels and valves. Estimation and management of availability in a complex operating facility is a challenging task, requiring the use of modern tools, engineering algorithms and engineering experience. In this research, we have developed some novel techniques to address availability using Markov-based state dependent models, risk based strategies, fault detection and its management along with maintenance scheduling optimization.

This dissertation is organized based on the above-mentioned focus areas. Chapter 1 is focused on introduction and overview of availability estimation and management. Some basic availability, risk and reliability concepts and definitions are also discussed in this chapter. The concept of PAM is vital and a foundation to the overall Availability Management (AM) process. AM mainly comprises two main components; one is asset maintenance management and the other is asset performance management is also part of this Chapter. In Chapter 2, a risk-based stochastic modeling approach based on the Markov Decision Process (MDP) is discussed to estimate availability of a plant. A model is developed based on critical equipment of a system to estimate overall processing unit availability. The developed model is applied on a gas absorption process to ensure its application on real-world problems. Chapter 3 describes a novel risk-based failure assessment approach to address the safety and availability of complex operating systems.

A structured process is proposed and validated using real-world failure assessment cases to prove the applicability and efficacy of the proposed model.

In the next Chapter, early fault detection and management is explained to support availability and safety improvement. Decision Trees (DTs) are introduced as a predictive data mining tool to detect early faults and their management to improve system availability. To conclude the effectiveness of the model, the proposed model was successfully tested to detect faults using real plant machinery vibration data. As discussed earlier, maintainability is important in availability management and so maintenance and its optimization is considered in this research. In Chapters 5, multi-constrained, multi-objective maintenance scheduling optimization models are proposed. The optimization problem was developed considering the time-dependent equipment failure rate to optimize maintenance costs at different availability and reliability levels. These models were applied on a plant scenario to show the effectiveness of maintenance scheduling optimization on cost, availability and reliability.

Finally, Chapter 6 concludes the research with the key findings, contributions and suggests possible expansion ideas for this work.

1.2 Research Objective and Scope

Availability is an extremely important parameter to ensure the continuous operation of facilities. Due to its importance and usefulness in asset intensive industries, we focused on developing comprehensive methods and models for availability estimation and management. These new methodologies and models mainly help to address the critical issues of unwanted breakdowns in processing facilities. These breakdowns have severe financial consequences along with adverse health, safety and environment consequences. There are many ways to estimate and improve availability, as presented in the next Chapters. We proposed some new models and algorithms, which can help improve and manage the availability of a complex processing facility. Generally, processing facilities lose millions of dollars in lost production due to unwanted breakdowns or interruptions, this research effort is a great resource to minimize such losses by properly utilizing these developments.

Figure 1.1: Overall research strategy

The specific objectives of this research are to develop effective and novel availability estimation and management methodologies for complex processing systems.

This research objective is realized by working on the following areas as presented in Figure 1.1.

a. Developed a physical asset management model and integrate for availability.
b. Developed a state dependent risk-based availability estimation method using the Markov method.
c. Developed a risk-based failure assessment framework to address safety and availability.
d. Developed model for early fault detection and management to enhance availability.
e. Developed multi-objective maintenance scheduling optimization models to enhance availability and reliability goals.

1.3 General Terminology and Definitions

To better understand the concepts in this dissertation, basic definition and terminology is discussed below.

1.3.1 Operational Measures

Many different measures are being used in the industry to monitor the efficiency and effectiveness of the processes, equipment and maintenance. Some of the key measures are defined below:

1.3.1.1 Availability

Availability is to identify if the equipment or process is available at a given time to perform its intended function. Availability is a function of reliability and maintainability. There are many types of availabilities in literature so it is important to understand them to use them properly. Availability can be defined as,

"Ability of an item to be in a state to perform a required function under given conditions at a given instant of time or during a given interval, assuming that the required external resources are provided" [1].

Other definition of availability,

"It is probability that a system or component is performing its required function at a given point in time or over a stated period of time when operated and maintained in a prescribed manner" [2].

Availability is also a probability like reliability and maintainability. Availability, sometimes referred as Inherent or average availability is measured as,

$$A = \frac{Uptime}{Uptime + Downtime} \tag{1.1}$$

$$A = \frac{MTBF}{MTBF + MTTR} \tag{1.2}$$

Where MTBF – Mean Time between Failure

MTTR – Mean Time to Repair

The other forms of steady state availability depend on the definition of uptime and downtime, the brief discussion about them follows:

1.3.1.1.1 Achieved Availability

Achieved availability is defined as,

$$A_a = \frac{MTBM}{MTBM + M'} \tag{1.3}$$

Where, M'= Mean System Downtime, $MTBM$ = Mean Time Between Maintenance

In this form, M' is the mean system downtime and $MTBM$ includes both unscheduled and preventive maintenance and is computed as,

$$MTBM = \frac{t_d}{mt_d + {}^{t_d}/_{T_{pm}}} \tag{1.4}$$

Where, t_d= Unscheduled Downtime, T_{pm} = Preventive Maintenance Time

1.3.1.1.2 Operational Availability

Operational availability is defined as,

$$A_a = \frac{MTBM}{MTBM + M''} \tag{1.5}$$

Where M'' is determined by replacing *MTTR* with *MTR*. *MTR* is calculated using equation below,

$$MTR = MTTR + SDT + MDT \tag{1.6}$$

Where, MTR = Mean Repair Time, SDT = Schedule Downtime

1.3.1.1.3 Generalized Operational Availability

Generalized operational availability is;

$$A_G = \frac{MTBM + ready\ time}{MTBM + ready\ time + M''} \tag{1.7}$$

1.3.1.2 Reliability

Reliability is a qualitative aspect of the system or equipment that performs intended function when we need it. "*It is the probability of a non-failure over time*". It is ability of an item to perform required function under given conditions for a given time. One of the other industry accepted definition of reliability is;

"It is a probability that a system will perform its intended function satisfactorily for a specified period of time under stated conditions" [3].

Mostly reliability is expressed in percentage and measures by the term MTBF for repairable systems. The same is usually measured in MTTF for non-repairable systems like bearing and seals. Many quantitative measure of reliability are available and expressed as follows:

The distribution function is given by:

$$F(t) = 1 - R(t) = \Pr\{T < t\} \tag{1.8}$$

The probability density function:

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \tag{1.9}$$

with the properties;

$$f(t) \geq 0 \; and \; \int_0^{\infty} f(t)dt = 1$$

then,

$$F(t) = \int_0^{1} f(t')dt' \tag{1.10}$$

$$R(t) = \int_t^{\infty} f(t')dt' \tag{1.11}$$

The reliability function

$$R(t) = \Pr\{T \geq t\} \, for \; t > 0 \tag{1.12}$$

Since the area under the entire curve is equal to 1, both reliability and failure probability will be defined so that,

$$0 \leq R(t) \leq 1 \;\; and \; 0 \leq F(t) \leq 1$$

1.3.1.3 Maintainability

In general, Maintainability (M) is how quickly the equipment can be restored back to be able to perform its function. It helps in quantifying the repair and restoration time in case of an equipment failure or breakdown. Restoration process is a key in terms of understanding the process involved while a repair is required. The main areas which can slow down the restoration include, availability of the spares, availability of technicians, release of the equipment to perform maintenance and type of process. In order to optimize the restoration time, process must be evaluated as whole rather than only failed equipment.

The parameter using by the industry to measure the maintainability is MTTR. As per industry accepted standards,

“Ability of an item 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”[1].

1.3.1.4 Utilization

Utilization is simply a ratio between the actual produced compared to planned production. This ratio gives us an idea how well we are performing compared to the planned or sometime called nameplate capacity.

Mathematically can be written as Equation 1.13,

$$Utilization = \frac{Actual\ Production}{Planned\ Production} \tag{1.13}$$

1.3.1.5 System Categorization

There are two types of system, repairable and non-repairable. When a system fails to perform its intended function, this state usually termed as non-functional and denoted by state 0. The other scenario is vice versa and that is when the system is working as intended and represented by state 1. If a system can be brought back from a failed sate to a functional state, the system categorizes as repairable system like compressor, pumps, and mechanical seals. In other condition, if the system cannot bring back into its functional state after failing the system is categorized as non-repairable systems, for example, bearings and gaskets.

1.3.1.5.1 Repairable System

Repairable systems are the systems where we repair the system when fail. It usually has many changes in states from function to non-functional state as can be seen in Figure 1.2.

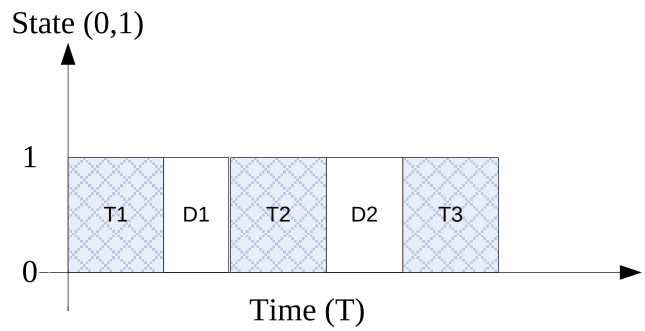

Figure 1.2: Repairable system

As discussed earlier, MTBF is the functional time (T1+T2+…) when the system is in state 1, i.e. functional time divided by the total time (T1=T2+T3+D1+D2+D3….). Similarly the down time is the non-functional time (D1+D2+…) divided the total time. The failure rate is estimated by using Equation1.14.

1.3.1.5.2 Non Repairable System

Non repairable systems or components have two states while using in a plant. The first is functional (working 100%) and other one is non-functional or failed state. Consider a system that is functional at time 0 and failed at time T, the life of the system or component will be T. State '0' and '1' represents the failed and function state, as illustrated in the Figure 1.3. The failure rate of this system is estimated by Equation 1.15.

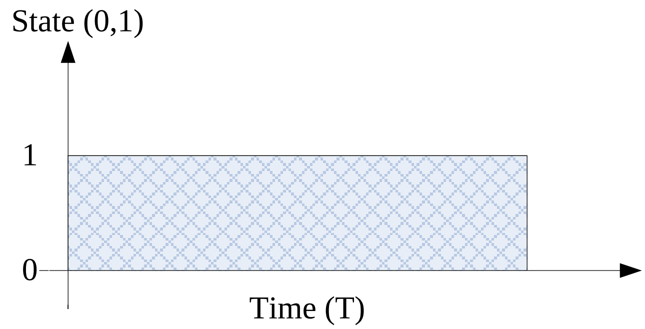

Figure 1.3: Non repairable system

1.3.2 Basic Terminology

Asset: Asset is defined as a formally accountable item [4]. In operation view, it is an item which intent to perform a function to support the process.

Criticality: A relative measure of the consequence of a failure mode and its frequency of occurrences [4].

Failure: Failure is termination of the ability of an item to perform a required function [1]. There are many ways to declare that the asset is in failed state and mostly depends upon the criticality of the operation. Failure can be complete or partial (degraded function).

Another interesting definition; failure can be defined as any change in a machinery part or component which causes it to be unable to perform its intended function or mission satisfactorily. [5]

Failure Rate: In simple words, it is a measure to observe the failure frequency of an equipment or component over a period of time. It is also defined as, a rate at which failure occurs as a function of time [6]. It is denoted by a symbol λ in this proposal.

For repairable systems,

$$\lambda = \frac{1}{MTBF} \tag{1.14}$$

For non-repairable systems;

$$\lambda = \frac{1}{MTTR} \tag{1.15}$$

Repair Rate: It is a rate that an out of service component will return in service mode during a given interval. [7]

Unavailability: It is a probability that item or equipment is not in functioning state. [6]

Mean Time to Failure: It is a basic measure of reliability for non-repairable items [4]. The total number of system life units, divided by the total number of events in which the system becomes unavailable to initiate its mission during a stated period of time. It is denoted by MTTR.

Mean Time between Failures: A measure of system reliability parameter related to availability and readiness [4]. The total number of system life units, divided by the total number of events in which the system becomes unavailable to initiate its mission during a stated period of time. It is applicable to repairable systems. It is denoted by MTBF.

Redundancy: In an item or system, the existence of more than one mean at a given instant of time for performing a required function [1].

Active Redundancy: Redundancy wherein all means for performing a required function are intended to operate simultaneously [1].

Standby Redundancy: Redundancy wherein a part of the means for performing a required function is intended to operate, while the remaining part(s) of the means are inoperative until needed [1]. It is often known a passive redundancy.

Parallel System: In parallel configuration, one the components in a system, must be in working condition to keep the system functional.

System reliability for a two component parallel system can be written as in Equation 1.16,

$$R_p = 1 - [(1 - R_1) \times (1 - R_2)] \tag{1.16}$$

Series System: In series configuration, any failure of a component in a system is a failure of the entire system.

System reliability for a three component series system can be written as in Equation 1.17,

$$R_s = R_1 \times R_2 \times R_3 \tag{1.17}$$

1.4 Literature Survey

This Section mainly focuses on the literature survey conducted on availability estimation and management, early fault detection to improve availability and the role of maintenance in asset management. Availability estimation and management is not only to ensure availability of processes but also other important aspects like safety, risk and safe operations are embedded in the concept. A detailed literature survey is carried out to highlight the research available in this area and the outcomes are given below.

1.4.1 Physical Asset Management[1]

The concept of physical asset management (PAM) provides a foundation of availability management and comprises management of assets such as machines and equipment in plants. PAM is a systematic approach for managing assets from concept to disposal; generally termed the asset life cycle. The purpose of a PAM system is to provide timely information to operations and maintenance personnel to safely increase the total production output of a plant at a reduced cost per unit of output. These benefits occur as the manufacturing facility makes optimum operating and maintenance decisions through the application of a PAM system information solution. Operation and maintenance (O&M)

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[1]*Section 1.4.1 is based on the published work in a peer-reviewed proceedings of a gas processing symposium, Attou, A.K., and Ahmed, Q. (2009), "Asset Management Practices at Qatargas," Proceedings of the 1st Annual Gas Processing Symposium, Elsevier B.V. To minimize duplication, all the references are listed in the reference list. The contribution of the authors is presented in Section titled, "Co-authorship Statement".*

personnel are constantly faced with decision-making based on limited information. PAM systems make this decision-making job easier by providing knowledge about the current and future condition of vital production assets. To achieve and meet production commitments, processing plants are increasingly turning to physical asset management as an optimization strategy to improve their process efficiency and reduce maintenance, and so enhancing their return on assets (ROA) [8]. It was noticed during literature survey that most of the work is performed by industrial experts in engineering magazines; and international technical journals have limited work available in this area. After realizing the opportunity, the University of Toronto started a physical asset management program, which is well received by industry due to the similar reasons for its usefulness and applicability. As discussed earlier, PAM can reduce maintenance costs, increase the economic life of capital equipment, reduce company liability, increase the reliability of systems and components, and reduce the number of repairs to systems and components. When properly executed, it can have a significant impact on an organization's bottom line [9].

Companies are reporting as much as a 30 percent reduction in maintenance budgets and up to a 20 percent reduction in production downtime or unavailability as a result of implementing a plant asset management strategy. Since as much as 40 percent of manufacturing revenues are budgeted for maintenance, these savings contribute significantly to the bottom line of a company. Manufacturers are now moving to implement such PAM strategies. Industries such as petrochemicals and utilities are aggressively moving ahead in adopting asset optimization principles [8].

The best PAM practices are the premier tools for maximizing availability, customer satisfaction, budget control, and a firm's edge over its competitors. In this Section, we present a PAM framework, experiences, and practices [10]. PAM is a combination of management, financial, engineering, and maintenance practices applied to physical assets to achieve low life-cycle cost. A structured approach is required to ensure the best management of assets. An important motivation for PAM is to achieve best-in-class reliability and availability, and maintainability of equipment.

It is important to focus on PAM from the early stages of design and development to reap the real benefits of the approach. Effective asset management typically produces a 20-30% reduction in maintenance cost accompanied by a 15-25% increase in throughput with no capital investment in equipment [11]. PAM can only be achieved by a team effort. Before discussing PAM practices, essential terminologies required to comprehend the PAM practices will be discussed.

It is a common misunderstanding to confuse asset maintenance management systems (AMMS) with asset performance management systems (APMS). In general, PAM covers a lot more than AMMS and APMS, but the scope of this Section is limited to discussion of the AMMS and APMS systems.

1.4.1.1 Asset Maintenance Management System

An AMMS contains information about equipment; its hierarchy in a plant; the manufacturers; technical and maintenance information including notifications; work history; and spare parts usage. This system is a foundation of PAM and provides information to APMS to monitor the performance using available data.

1.4.1.2 Asset Performance Management System

An APMS is a tool that provides us the flexibility to use the data in AMMS and makes it available for analysis. This system monitors performance, maintenance execution, equipment reliability, process reliability, and availability. The best way to perform this task is to integrate the system to retrieve data, in an asset-centric approach (ACA) as discussed in [10] and shown in Figure 2.1.

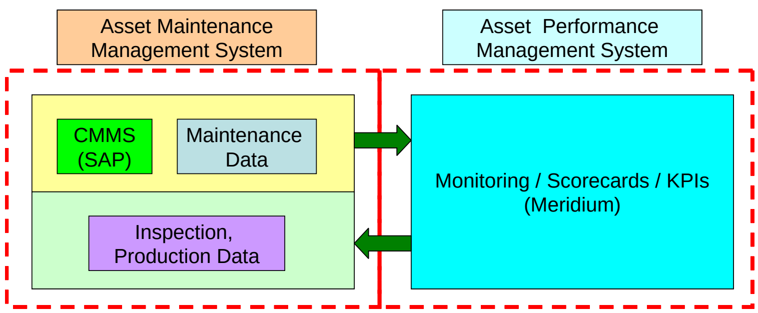

Figure 2.1: Asset Centric Approach

An asset centric approach is a requirement of AM to streamline the complete process [10]. It is important to have measurement data to manage and control the process. An APMS provides a platform to monitor performance, whereas AMMS presents a base to capture all the required data, which includes equipment data, maintenance data, and inspection data.

To implement a successful PAM, it is essential to focus on both AMMS and APMS, simultaneously. The PAM program mainly focuses on reliability and availability, which starts with comprehensive analysis generally referred to as gap analysis. The gap analysis enables a company to identify its shortcomings. It also provides an estimate to determine an assignment, which not only fulfills such shortages but also helps optimize the firm's AM. Likewise many industrial analyses, including gap, availability, and reliability analyses are data driven. Therefore, precise data collection is essential to achieve desired outcomes from these analyses.

An AM program has many components, including AMMS and APMS. The components are shown below:

- ***Asset Maintenance Management System***
    - Data Integrity and Quality
    - Maintenance Strategies
    - Condition Monitoring System

- ***Asset Performance Management System***
    - Utilization of Data from AMMS
    - Reliability Analytics
    - Root Cause and Failure Analysis Program
    - Loss Production Events
    - Scorecards, KPIs

The general strategy to implement PAM in a plant follows the five key steps. A graphical representation of these key steps is shown in Figure 2.2.

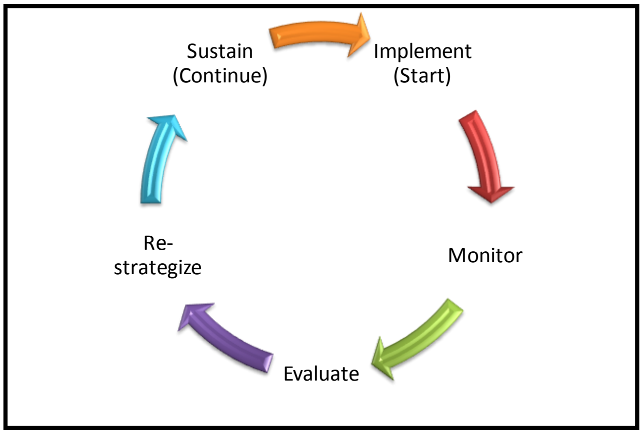

Figure 2.2: General strategy – five key steps

Besides the above mentioned steps, progressive teamwork is essential to a successful AM program. True success from a PAM program is foreseeable when a firm adopts a culture of continuous improvement.

This Section briefly discusses the AM practices benefits to natural gas processing facilities. This effort comprises development of PAM and its implementation, including benefits and challenges. A significant improvement of availability is experienced with the implementation of PAM methodology. PAM provides a solid framework to estimate and manage availability. This Section also deals with the benefits and challenges experienced during implementation of PAM [10].

The benefits that are realized with the implementation of PAM framework:

i. Provides an up-to-date database with maintenance and equipment information
ii. Helps with maintaining lower running costs for the plant
iii. Improved availability and reliability (95-98%)
iv. Proactive rather reactive approach to solving problems
v. Higher profits and customer satisfaction
vi. KPIs and scorecards to monitor performance

Some of the challenges are also identified; outcomes can be improved by addressing them properly at an early stage of the implementation process.

i. Data capturing, integrity, and quality
ii. Integration among different systems
iii. Cross-function team interaction
iv. Upstream and downstream availability models

1.4.2 Risk and Risk-Based Assessment

To efficiently utilize resources and target poorly performing equipment, risk-based approaches have been utilized by companies. In these methods, risk is usually evaluated to identify the action to mitigate them. Chemical processes have great potential for random equipment breakdowns, system unavailability, production losses, toxic releases, fire or explosions. Probability of occurrence and the consequences generally are primary drivers of risk analysis for unwanted events. Kaplan and Garrick define risk of an event as a set of scenarios, each of which has a probability (likelihood) and a consequence [12]. The likelihood is expressed either as a frequency (i.e., rate of an event occurring per unit time) or as probability (i.e., the chance of an event occurring in defined conditions), and the consequence is referred to as the degree of negative effects observed due to occurrence of an event. To facilitate the risk assessment process, many companies have developed a risk assessment matrix to quantify risk and its consequences as a baseline to identify actions to mitigate risk events based on the overall risk.

In general, risk can be calculated using the equation,

$$Risk\ = Probability\ of\ failure\ \times Consequence \tag{1.18}$$

Risk-based methodologies are commonly used in research and industry to optimize inspection and maintenance intervals, which maximizes a system's availability based on risk. The methodology presented here is comprised of two steps: (i) Availability modeling and (ii) risk-based inspection and maintenance calculations. A risk-based approach is also helpful in making decisions regarding prioritization of the equipment for maintenance and determining appropriate maintenance intervals. The proposed method in this work is applied to a steam generating system of a thermal power plant. Risk analysis has been part of a standard operation requirement in the offshore industry for many years. Analyses are most effective when they are integrated into design work and planning of operations [13]. Risk-based approaches are effective in managing cost, resource planning and return on investment. They are also effectively used in shutdown management to improve plant reliability and maintain it above a minimum operational reliability [14].

1.4.3 Availability Estimation

Availability estimation is a critical parameter in all aspects of managing equipment in a plant. It is a main driver for maintenance, operations and others to plan their respective work. It includes all equipment and systems, and is not limited to production, engineering, commercial activities and shipping, safety, and machinery. Its importance is further enhanced by the fact that maintainability with reliability determines the availability of a plant. A plant must be reliable and easily maintainable to ensure maximum availability, and should be equipped with the resources needed to bring it back online in the shortest time in case of any failure. Availability is also important in communication networks and power networks. In this work, availability models of high-availability communication networks are discussed. Models were developed to estimate the effectiveness of radio communication link in achieving its purpose of availability estimation [15].

Availability estimation is vital in planning, maintenance and production of the processing plant. We will explore some the work performed in the area of availability estimation in this Section. Most of the equipment in a plant belongs to a repairable system category and an efficient approach to estimate the availability of the repairable system within a fixed time period in this work. [16]. Beta distribution has been used to estimate system availability. The authors applied the proposed model on an IT system. This system is providing a service to users, where availability is one the critical parameters for monitoring and control. In another effort, availability estimation for an iron ore production system was performed using simulation. Simulation was used to ensure that the system has enough redundancies to meet the production requirement [17].

Performance of mining equipment depends on the reliability of the equipment used and many other parameters like maintenance efficiency, environment, and operator capability. Reliability analysis is required to identify bottlenecks in the system and to estimate the reliability of the system for a given designed performance [18]. In this work, parameters of some probability distribution such as Weibull, Exponential and Lognormal distribution have been estimated using software. The reliability of critical systems was identified, which proved to be the main bottleneck in achieving availability of plants.

Modeling of availability for a reliability-based system using Monte Carlo simulation and Markov chain analysis is presented in this paper [19]. Operational availability, which is dependent on the mean time to repair and administrative logistic time, was assessed using breakdown maintenance and scheduled maintenance. The authors have used the continuous Markov chain analysis for evaluating the probability of each transition state.

Bayesian estimation of reliability rates was used to estimate the LNG chain availability [20]. LNG plants usually have very high investment and operating cost. Improvement of reliability of a LNG chain will lead objectively to a substantial decrease of energy costs. It is difficult and challenging to model big systems, like LNG chains, because of their physical dimensions. In this research a systematic approach is used to discuss the space of the phases. A bottom-up technique was utilized to constitute the global model of reliability of the chain. A Bayesian estimation approach is used to define failure and repair rates for the equipment. Errors in steady-state availability estimation by 2-state models of one-unit system, which can be represented by 3-state Makovian models, are evaluated. It has been concluded that the 2-state models result in large errors for the case in which degraded systems are not repaired, and so multistate models should be used [21]. Computer simulation is very common in industry to estimate availability and research was conducted to estimate the availability of a cement plant. Availability is estimated using the physical configuration of work stations, failure and service time distributing including buffer storage as inputs [22].

Classical statistical estimation techniques have limited usage in predicting system availability when a system is highly reliable like a computer. In this work, a Bayesian solution is suggested to derive both steady-state and instantaneous availabilities [23]. In refineries and chemical processes, decision making is based on the availability of the components and entire system. The use of Petri net simulation is common in availability analysis. In this work, an alternative generic Markov model is used to predict availability and reduce computational efforts by orders of magnitude [24]. Steady-state series availability details the importance between the "product rule" and the "correct availability" [25]. The failure pattern of repairable systems is often modeled by an alternating renewal process, which implies that a failed component is perfectly repaired. In practice, this is not true. The paper proposes a generalized availability model using general distribution, which is different from a new component [26].

1.4.4 Availability Management

Availability management is an important aspect of this research. Importance of availability management can be understood by the fact that it is not possible to reap the real benefits if the life cycle of equipment and plants is not managed properly. Management involves different strategies from design to disposal and must be implemented in a specific order. Availability is the most valuable parameter because it encompasses reliability and maintainability. Returns on investment can be maximized simply by properly managing the availability. In general, this area requires more focus as it is lacking in published research work. This is due mainly to being less analytical in nature and more related to development of processes and managing them properly.

Extensive research is available on asset management (AM) but most of the work is published in professional magazines and consulting company websites. Limited AM work has been published in technical research journals. In this work, the basic elements of the availability management methodology in complex technical systems are discussed. This methodology primarily relates to information technology systems. The result of the implemented technology enhances the availability level through the clear identification and elimination of critical elements that affect the stability of IT infrastructure and ensures a continuing service provided by the system [27], and so the AM process should be given an appropriate level of service. In other work, an availability management framework (AMF) is presented to support the flexible management of availability for large distributed systems using object-oriented framework technologies. AMF flexibility is used to accommodate changing availability requirements, which vary with each application [28]. In a review by

ABB automation technologies, various aspects of ABB's life-cycle management program for improved product and system availability is discussed. ABB has created a life-cycle management program that ensures customers get the best possible return on their assets and benefit from a smooth transition to new generations of products [29]. A new approach to integrate reliability, availability, maintainability and safety is presented. This approach covers all phases of product development and is aimed at complex products like safety systems. The proposed approach is based on a new life-cycle model for product development and integrates this model into the safety life cycle of IEC 61508 [30]. In this paper, a result of applying the framework to support availability of an RFID system is also discussed.

1.5 Constraints and Limitations

A considerable effort has been made by researchers and industry experts in the area of availability estimation of repairable systems and equipment, but the literature on availability management is limited in technical journals. One of the reasons for this research is the importance of availability of the system and its application in industry. The concept is applicable to almost all the industries including IT, airlines, medical, and gas processing. The proposed work mainly focuses on the petrochemical or gas processing plant availability estimation and management, so the objective of this Section is mainly to identify the constraints and limitations within this domain.

Data availability and quality are keys to such quantitative analysis. Regardless of its key role in such studies, unavailability of good quality data is one the biggest challenge researchers face when estimating the availability and reliability of systems. In this case, because of the same reason, a Bayesian approach was used to define the failure rates and repair rates of different equipment [20]. In the processing industry, the issue of nonexistence of data is critical [31]. Researchers are using engineering judgments with available data like OREDA, EXIDA, and other data sources. It is challenging to use existing data. In case of the OREDA, the data is based on offshore equipment, where the failure modes are different from the similar equipment installed onshore. Extreme care must be practiced when using this type of data in validating the proposed models.

Risk is also difficult to calculate because the probability of failure is dependent upon the quality of the data. As discussed earlier, risk is a product of probability of failure and the consequence of an event. If the probability calculation is based on poor data, there is a great chance that all effort can go to waste. Data analysis usually describes statistical manipulations, which are carried out on raw failure data to provide estimates of component reliability and availability. All the data analysis gives only limited information if no proper risk assessment is performed. To determine the safety, reliability, and availability implications, a proper risk analysis required [32].

To address the above challenges, we have taken extreme care in data collection, cleansing and analysis. In certain cases, consultation with subject matter experts, along with personal field experience, was used to ensure the correct data is used in developing and validating the developed models.

1.6 Thesis Structure

This thesis follows the objective sequence as discussed earlier. The Chapter structure is discussed below:

- Chapter 1 provides a brief introduction to physical asset management (PAM); operation measures like availability, reliability, and maintainability; and other basic terminology. Section 1.4.1 has detailed discussion on physical asset management. It attempts to answer why PAM is important and also emphasizes its relationship with cost, maintenance, and availability management. This Chapter also focuses on assumptions and limitations; research objectives; a brief literature survey; and the dissertation structure.
- Chapter 2 discusses the overall risk-based availability estimation process using Markov method. This Chapter includes an introduction to Markov modeling, its usefulness, and limitations. State models and other modeling work are included in this Chapter. Analysis results and validation using the gas absorption unit is also covered.
- Chapter 3 describes a novel risk-based failure assessment approach to address the safety and availability of complex operating systems. A structured process is proposed and validated using real-world failure assessment cases to prove the applicability and efficacy of the proposed model.

- Chapter 4 explored early fault detection and management to support availability and safety improvement. In this Chapter, decision trees (DTs) are introduced as a predictive data mining tool to detect early faults and their management to improve system availability. To conclude the effectiveness of the model, the proposed model was successfully tested to detect faults using real plant machinery vibration data.
- Chapter 5 mainly focuses on multi-constrained, multi-objective maintenance scheduling optimization. The optimization problem was developed considering a time-dependent equipment failure rate to optimize maintenance costs at different availability and reliability levels. These models were applied on a plant scenario to show the effectiveness of maintenance scheduling optimization on cost, availability, and reliability.
- Finally, Chapter 6 concludes the research with the key findings, novelty and contributions and suggests possible expansion ideas for this work. This Chapter also discusses the learnings from this research work and its contribution toward improvement of industrial issues.

CHAPTER 2

RISK-BASED AVAILABILITY ESTIMATION USING A MARKOV MODEL [2]

Abstract

Asset intensive process industries are under immense pressure to achieve a promised return on investments and production targets. This can be accomplished by ensuring the highest level of availability, reliability, and utilization of critical equipment in processing facilities. To achieve designed availability, asset characterization and maintainability play a vital role. The most appropriate and effective way to characterize the assets in a processing facility is based on risk and consequence of failure.

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[2] *This Chapter is based on the published work in a peer-reviewed journal. Qadeer Ahmed, Faisal I. Khan, Syed A. Raza, (2014) "A risk-based availability estimation using Markov method", International Journal of Quality & Reliability Management, Vol. 31 Iss: 2, pp.106 – 128. To minimize the duplication, all the references are listed in the reference list. The contribution of the authors is presented in Section titled, "Co-authorship Statement".*

In this Chapter, a risk-based stochastic modeling approach using a Markov Decision Process (MDP) is investigated to assess processing unit availability, which is referred to as the Risk Based Availability Markov Model (RBAMM). The RBAMM will not only provide a realistic and effective way to identify critical assets in a plant but also a method to estimate availability for efficient planning purposes and resource optimization. A unique risk matrix and methodology is proposed to determine the critical equipment with direct impact on the availability, reliability, and safety of the process. A functional block diagram is then developed using critical equipment to perform efficient modeling. A Markov process is utilized to establish state diagrams and create steady-state equations to calculate the availability of the process. The RBAMM is applied to the natural gas (NG) absorption process to validate the proposed methodology. In the conclusion, other benefits and limitations of the proposed methodology are discussed.

Acronyms and Abbreviations

Symbol/Abbreviation	Description
A_S	System Availability
A_U	Unit Availability
A_{SS}	Availability – System Static Equipment
A_{SR}	Availability – System Rotating Equipment
HP	High Pressure
LP	Low Pressure
MDP	Markov Decision Process
MTBF	Mean Time Between Failures
MTTR	Mean Time to Repair

OREDA	Offshore Reliability Data
μ	Repair Rate
RA	Risk Assessment
RAM	Risk Assessment Matrix
RBAMM	Risk Base Availability Markov Model
RBD	Reliability Block Diagram
SR	System Rotating Equipment
SR_n	Subsystem in Rotating Equipment
SS	System Static Equipment
SS_n	Subsystem in Static Equipment
SHE	Safety, Health, and Environment
λ	Failure Rate

2.1 Introduction

In the processing industry, high availability and reliability are the means to effectively utilize and manage processes, equipment, and other resources. This is done to ultimately improve the return on investment (ROI) for all stakeholders with management of cost, lowest dangerous emission levels, and highest safety. In recent years, fierce competition and slim margins have driven economies of scale; companies are trying to integrate and manage processes while utilizing excess capacities available in other places to improve upon the availability of the plant. It becomes very critical in the processing industry to focus on the reliability and availability of the plant to ensure fulfillment of the global sales commitments with other visionary objectives. In general, availability can be defined as probability that a system or component is performing its required function at a given point in time or over a stated period of time when operated and maintained in a prescribed manner [1]. There are many ways to measure and estimate the availability and reliability of the systems and products. In this work, a processing unit is comprised of many subsystems incorporating many pieces of equipment. To work on such systems, there are certain ways to calculate the availability and reliability of the systems. The availability of the process has embedded reliability and maintainability of the equipment, as in Equation 2.1 and Equation 2.2. To work on availability enhancement and estimation, focus must be given to both reliability and mean time to failure. Improved availability can be considered as improved reliability and maintainability. Availability, sometime referred as inherent or average availability, is measured as:

$$A = \frac{Uptime}{Uptime + Downtime} \tag{2.1}$$

$$A = \frac{MTBF}{MTBF + MTTR} \tag{2.2}$$

Processing systems usually consist of many types of equipment, with different redundancies and architecture to achieve the required level of functionality and availability. For example, in gas liquefaction systems, the gas is converted into liquid by cooling it down to a -160°C temperature, and numerous compressors, turbines, motors, vessels, and valves are utilized to attain this objective [2]. The calculation of availability and reliability is not an easy task in this type of configuration due to the large equipment base [3]. There are tools and methods that can be utilized effectively with engineering experience to estimate such parameters. In general, availability can be estimated by considering all the equipment in a processing unit or plant; given the fact that there are numerous maintainable pieces of equipment in a processing facility, a detailed monitoring of all equipment is usually a prohibitive task. In addition, such an investigation of equipment would engage large amounts of resources both in terms of monitoring systems and personnel. With all the effort, it may not result in an optimal solution in real-time even with such substantial investment. But this problem could be solved by using a risk-based assessment approach that is very effective in identifying the critical systems and handling them appropriately in a processing plant, as presented in this Chapter.

The goal of this work is to develop a risk-based modeling technique for a continuous gas processing unit to calculate availability using a Markov methodology and applying the model to estimate the availability of the gas sweetening Section of a plant, as in Figure 2.4. The proposed research offers four distinct contributions: first, a risk-based assessment approach is introduced to identify the most critical components in a typical plant. Second, using the outcomes of the risk-based assessment; a stochastic modeling approach based on the Markov Decision Process (MDP) is utilized to develop models that estimate plant availability. Third, the models developed are calibrated on a gas processing unit with available plant data and offshore reliability data (OREDA). Lastly, bottleneck and limiting factors affecting availability will be identified with the benefits of the proposed methodology.

2.1.1 Literature Review

In the literature, extensive work on availability and reliability modeling is available on repairable equipment but very limited application of full system modeling is observed in the process industry, i.e., gas processing and other petrochemical facilities. Due to interest and opportunity, the topic was considered as a means to develop a methodology to estimate the availability of a complete processing network or unit rather than a single piece of equipment or a single system. For example, the availability estimation of a gas compressor as single equipment can be performed easily compared to the complete liquefaction unit in a gas processing facility.

Availability is widely used in a very generic sense in the existing literature. Many authors have worked on different availabilities like operational availability, achieved availability, and inherent availability. Simply, availability is a probability that a system will be operational when needed to serve a purpose and this usually is termed inherent availability [4]. Availability has a strong relationship with reliability and maintainability. Khan et al. [5] proposed a risk-based methodology to maximize a system's availability by considering the modeling and risk-based inspection/maintenance calculation. The discussed methodology is based on two steps: (i) availability modeling and (ii) risk-based inspection and maintenance calculations. Maintainability has vital importance in operational availability. Sonawane et al. [6] discussed operational availability where the mean time to repair and administrative logistic time are important.

Markov analysis is one the many techniques in the literature used to calculate availability and reliability of multi-state repairable systems. Pil et al. [7] used a time dependent Markov approach to evaluate the reliability of the re-liquefaction system and developed a maintenance optimization model and applied it to the re-liquefaction system. Keeter [8] discussed the availability of powerful computers to run long and extensive models for availability and reliability calculations. These tools have enabled us to understand the gain achieved from improving equipment reliability, and also other benefits like asset utilization. Jacob et al. [9] explored the difficulties in determining reliability and availability for repairable and non-repairable systems. The analysis is difficult when the failure distribution is not exponential and becomes even more difficult when the systems are hybrid and complex rather than only series, parallel or a combination of two. In his work, Jacob presents a binary decision diagram to calculate a system's reliability and availability.

Moore [10] pointed out that mechanical availability as a function of maintenance cost under different maintenance strategies, i.e., the mechanical availability, will be lowest in reactive strategies and highest in reliability-focused maintenance strategies. Mobley et al. [11], stressed that availability differs slightly from utilization; the main difference is that the scheduled run time varies between facilities and is changed by factors such as schedule maintenance action, logistics and administrative delays. Ouhbi et al. [12] utilized a semi-Markov system to estimate the reliability and availability of a system and applied it on turbo-generator's availability and reliability estimation. Cekyay et al. [13] presented a work to analyze mean time to fail and availability of mission based system under maximal repair policy. Csenki [14] explored the concept of work mission availability to approach the cumulative operational time. Two methods of availability estimation and capacity distribution have been discussed [15]. The first method is based on capacity outage probability tables, and although estimations performed by this method are exact they have limited applications. The second method is based on a probability mass function series, which is computer intensive but the results are better with increasing computation. An optimal reliability, availability and maintenance management strategy is presented to optimize the service levels with minimal cost [16]. The focus is on inventory management and a new model has been introduced to improve the service level, which only covers the maintainability part of the scope. Availability assessment of offshore oil and gas fields reveals that the equipment failure and production losses can exceed the allocated budget [17]. This work explores the probability distribution of downtimes and random equipment failure in design optimization to improve availability of the production systems. Genetic algorithms have been used to optimize the availability of the equipment [18]. The availability optimization was done using different project costs, weight, and availability of maintenance workforce. The proposed model is a novel and practical contribution, which presents the risk-based availability estimation using state dependent models.

2.1.2 Brief LNG Process

Liquefied natural gas (LNG) is a liquid form of natural gas. This state of gas increases its marketability and makes it feasible for transportation around the globe for utilization in power generation, households and other applications. In liquid form, the temperature of LNG is usually around -160°C and the volume is around 1/600 times of the gas at room temperature. It is colorless, odorless and non-corrosive in nature. LNG is cryogenic liquid, which means it can be kept in liquid form at temperature -160°C with the condition of constant pressure [19]. Once LNG arrives at a receiving terminal, it is usually re-gasified to use in the industry and homes. An LNG process plant is asset intensive and a great deal of safety is necessary to ensure a safe work environment. In the same context, availability is also vital to guarantee meeting customers' demands around the globe by producing as per schedules. A general LNG manufacturing process consists of following several major steps. Raw gas is received from a reservoir to the inlet receiving area, which is followed by treatment (removal of corrosive and hazardous contents), liquefaction of natural gas, storage, shipping of the LNG and finally the regasification at the receiving end for use. The simplification is shown in block diagram Figure 2.1.

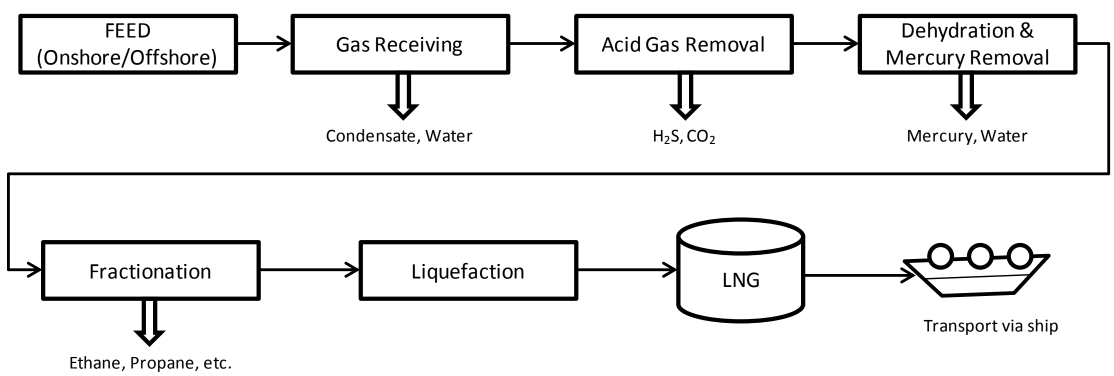

Figure 2.1: Simplified LNG process flow

Generally, from the reservoir, a three-phase feedstock is sent to the onshore receiving area where the gas, condensate and water are separated. Gas usually contains many hazardous and non-hazardous elements, which in most cases must be removed prior to natural gas (NG) liquefaction. These elements are usually sulfur in the form of hydrogen sulfide, carbon dioxide, water, helium, mercury, other sulfur species and heavy hydrocarbon. The NG feedstock is treated to remove sulfur and water. Other contaminants like mercury and mercaptan are removed from the gas prior to the liquefaction process. Liquefaction of natural gas is a physical process that is achieved by successive cooling through exchange of heat using refrigerants. LNG is stored in full containment tanks that are heavily insulated to minimize the heat transfer and boil-off of the liquid. LNG is shipped through special ships to the destination where it is re-gasified for use in power generation and returned into country's gas circuit for home and other domestic use.

2.2 Risk and Risk Assessment

Risk and criticality are two synonyms often used in the oil and gas industry. Risk can be defined in many ways; simply put, it is the likelihood of an unwanted event times its unwanted consequence [20]. Risk assessment (RA) is an engineering process of performing a cross-functional team-based analysis on functions, systems and equipment to evaluate the risk of a given situation or scenario. In this research, a unique risk assessment methodology is proposed to effectively select the critical equipment affecting the function of a system, hence affecting availability. RA is foundation to the proposed research. Different companies have different exposures to risk depending upon their business, geographical location, and financial structure and so on. They develop mitigation plans based on the riskiness/criticality of an unwanted event to avoid them. It is also very important to understand why the risk assessment is being performed so that attention may be focused on the right consequences. For example, the oil and gas industry has different financial risks due to its asset intensiveness and price fluctuations compared to other industries, especially those that do not have physical assets. The industry also has operating risks and hazards because of high operating pressure and low temperatures. These operating parameters have severe consequences in case of equipment failure. The risk assessment approach developed in this research to estimate availability is unique because the approximation of risk is established using consequences like reliability and maintainability along with others. The advantage of this approach will provide the benefit of keeping focus on the categories that directly affect the availability, including others like safety, health, and environment (SHE), and economics. The main objective of the company is to identify the risk and develop mitigation plans to address the critical scenarios to as low as reasonably possible (ALARP) levels. It is not possible to bring the risk to zero, so importance lies in assessment, mitigation plan and management of risk. Literature and other standards have defined risk in many ways. The most useful and widely applicable definition of risk is as follows: “Risk is a measure of potential loss occurring due to natural or human activities” [20]. Another meaning of risk is a “measure to human injury, environmental damage or economic loss in terms of both the incident likelihood and the magnitude of the loss of injury” [21].

The outcome of the risk assessment establishes that either the scenario or equipment is critical. Riskiness is also known as criticality. The criticality number is a measurement used to establish whether the assessed scenario or system is critical or not. If the system is critical, it has to be managed properly to ensure plant target availability. Usually, different companies have different methods to evaluate risk. One of the most common methods is to evaluate risk using a risk assessment matrix, as shown in Figure 2.2. We used the risk assessment matrix with four important consequences categories, including: HSE, Economic (business loss/maintenance cost), Reliability, and Maintainability. It is very common in the industry to evaluate risk using the first two consequence categories, but the uniqueness of this risk assessment comes from the consequence categories of reliability and maintainability, which helps identify the assets that really affect or can affect the availability of the equipment or processing unit. The details of the risk categories are explained in Section 2.4.2 of this Chapter. The level to accept risk or level of classification, i.e., high, medium, or low, depends upon the company management, regulations and other requirements. The criticality zones shown in the assessment matrix are simply guidelines; every company has its own risk assessment matrix and defined risk boundary.

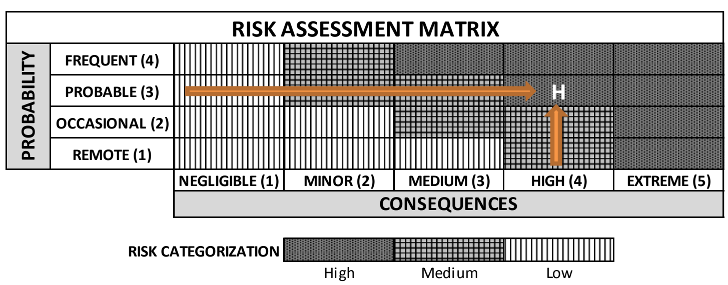

Figure 2.2: Risk assessment matrix

Higher consequences mean higher risk and criticality. As an example, if the consequence is as high as 4 and the probability of the incident is probable as 3, the risk is high, as shown in Figure 2.2. If the risk is high and the potential threat to the company's business or society is high, it must be assessed properly. Risk analysis is mainly used to estimate the magnitude of a potential loss and can be done by using qualitative or quantitative analysis or combination of both terms as mixed qualitative-quantitative risk analysis [20]. The criticality risk may vary for different companies depending upon the business; a petrochemical plant may have different criteria for classification than a LNG plant. Risk is often expressed as a function of the frequency or probability of the incident and consequence of the incident, as shown in Equation 2.1 and 2.2.

$$Risk = \text{Probability of failure} \times \text{Consequence} \tag{2.3}$$

$$R = P \times C \tag{2.4}$$

Individual risks can be calculated using the following equations:

$$R_{SHE} = P \times C_{SHE} \tag{2.5}$$

$$R_E = P \times C_E \tag{2.6}$$

$$R_R = P \times C_R \tag{2.7}$$

$$R_M = P \times C_M \tag{2.8}$$

Overall risk, R, can be selected using Equation 2.9.

$$R = R_{SHE} \times R_E \times R_R \times R_M \tag{2.9}$$

where, R = Overall risk due to unwanted event, P = probability of failure, C = Consequence, R_{SHE} = Risk due to SHE consequence, R_E = Risk due to Economic consequence, R_R = Risk due to Reliability consequence, R_M = Risk due to Maintainability consequence.

The output of the risk assessment is a categorization of equipment causing functional failure of a system, unit or equipment. In this research, risk has been categorized in three categories, high, medium, and low. Quantitatively, assessment can also be done using the numbers and selecting the biggest value as the max value as criticality. Once the ranking has been established, the critical equipment within a system can be chosen and functional block diagram should be developed to move forward toward a Markov model, as discussed in the framework in Figure 2.3.

2.3 Risk-based Availability Modeling Framework

The risk based availability concept is based on identifying critical equipment which causes functional failure in a complex system or unit. Functional failure is an interruption in production and can be addressed using economic category of the risk assessment matrix. The proposed framework provides a unique way to identify critical equipment. Asset intensive unit can be simplified using the risk-based proposed methodology without violating the functional integrity of the system to estimate availability. The main advantage of this methodology includes but not limited to identifying the bottlenecks early in the process and addressing them to optimize resources and cost. Selected systems based on the risk will pinpoint the equipment that has a direct impact on availability. The system has many pieces of equipment but not all are critical and should be treated accordingly to balance the risk and available resources. We will further discuss in detail the Markov based model to estimate availability.

In order to keep the process consistent and effective, the following steps have been proposed in this research to develop the model to estimate availability. The graphical presentation of the complete process can be observed in Figure 2.3.

1. Selection of system / operating unit or plant: Develop a boundary diagram of the system to be studied, which helps team to be focused and prepared.
2. Establish a cross-functional team: Important in order to identify real critical equipment.
3. Develop or review existing risk assessment matrix to ensure all team members understand the consequence and probability categories.
4. Perform risk assessment: Ensure risk assessment is done in a cross-functional environment to identify critical assets.
5. Breakdown of processing unit into small units: After identification of all critical assets, we developed a functional model to place the equipment in the process functional flow sequence.
6. Develop functional block diagram to develop state diagram: In this step, a functional block diagram is developed using the previous step data and represents the architecture of the systems.
7. Develop a Markov model: State diagrams using functional block diagram are developed in this step; differential equations are established from the state diagrams.
8. Collect all required data: The main input of this data is from maintenance history and other available databases like OREDA [22].
9. Run the model using available failure rate and repair rate data.
10. Estimate availability: Individual subsystems and overall system availability can be estimated using the independent system data. The series and parallel systems are

dealt accordingly to estimate the final availability of the selected system or operating unit.

2.3.1 Modeling Technique using Markov Model

In general, mathematical modeling of systems is an area of great engineering interest and process modeling makes it even more challenging. It is not a simple task to calculate the availability of a unit with a higher number of equipment using individual equipment failure and repair rates. It is often a model using operating parameters like production loss, name plate capacity, and sustainable capacity to estimate operational availability and reliability. The conclusion is usually based on production rates rather than equipment failure rates. Technically, the outcome is operational availability rather than the process availability based on the failure date.

The above discussion can be explained further by this example: assuming that you are assigned to produce 100 tons in 30 days and you are able to produce 100 tons in a given period with a failure, your availability will be 100% even with a failure. The reason that the availability is still 100% is that the calculation is based on the production targets rather than using equipment MTBF and MTTF. The reason you were able to achieve 100% availability with a failure is that you have utilized your equipment beyond the normal operating window and were able to achieve the targets. It is indeed a very cumbersome process to model the complete system and use the real failure rates of equipment for estimation where the unit consists of thousands of functional locations. The proposed risk based methodology works great in these situations. Some limitations exist in the proposed

Markov methodology, i.e. constant failure and repair rates are independent events and the probability of being in any state depends upon the immediately previous state.

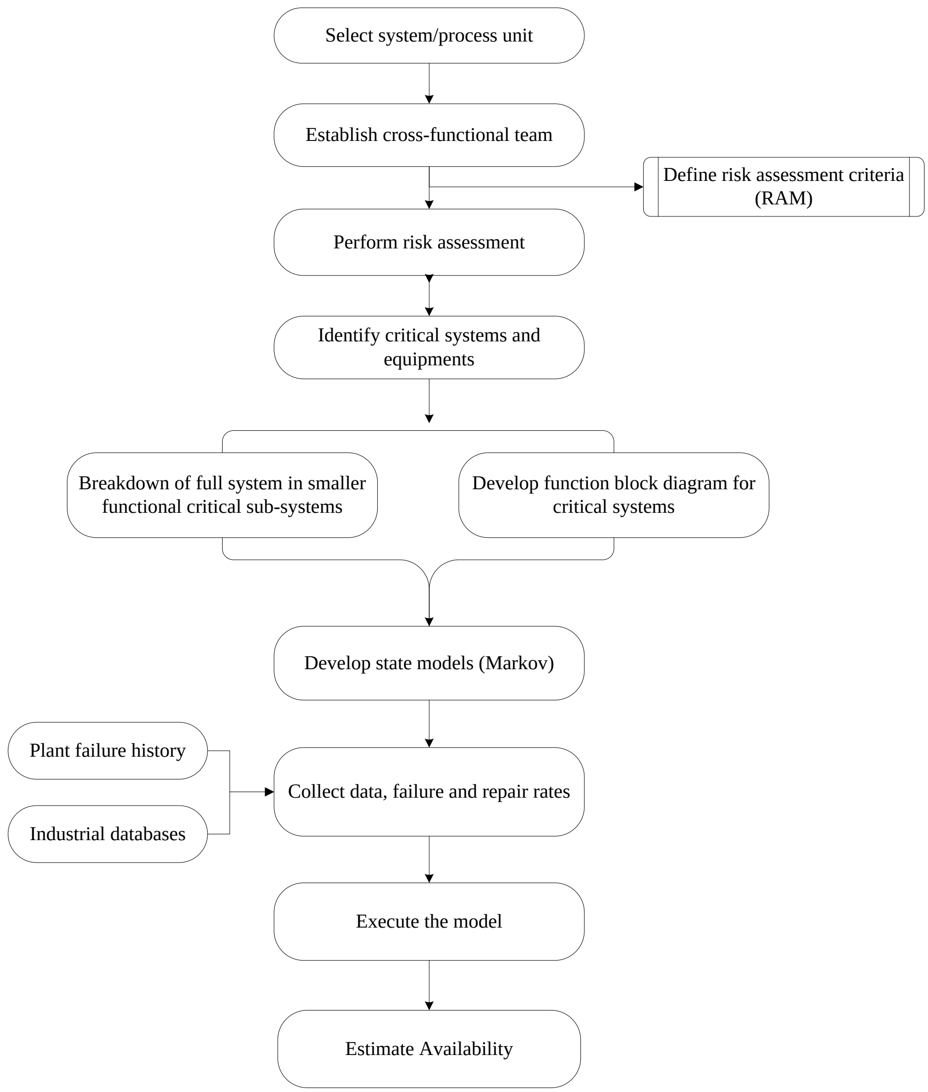

Figure 2.3: Flow diagram of risk based availability model

As discussed, we will use the failure and repair rates of the equipment and systems to estimate the availability. This is one of the reasons the risk based approach was adopted to handle the number of equipment and still obtain reasonable estimates to address the issue. Risk based approach plays a vital role by optimizing the resources and still achieves comparable results. If a model is developed using 100 pieces of equipment, state space goes very high and becomes very difficult to handle; as an example, if there are 100 pieces of equipment and each has 2 states, the total will be 2^100 and that would be around 1.3E+30 states. Quantity can be reduced or the problem can be simplified by breaking down the system into a series of independent subsystems [3].

In this research, we approach the problem from a user real experience angle and come up with a risk based approach to estimate process availability. Units have been broken down into smaller sub-systems to calculate availability, as shown in Figure 2.4. Markov based state dependent methodology is used to develop state models. A Markov model is a technique in which a system can be studied with several states, like operational, failure, and degraded. An approach is presented in this work to estimate the availability of the unit using different equipment and sub-system individual availabilities within the unit. State models have been developed using a real plant case, which helped us to model factual conditions. The proposed method provides a tool to solve the process, which will be discussed later in the methodology. A Markov model can be mathematically written as follows [10]:

$$\sum_{j} Rate\ into\ state\ i\ from\ j\ \times\ P_j = Rate\ out\ of\ state\ i\ \times\ P_i \tag{2.10}$$

If $P_i(t)$ is the probability of being in state i at time t, the summation of all probabilities can be written as follows:

$$P_1(t) + P_2(t) + P_3(t) + \cdots P_n(t) = 1 \tag{2.11}$$

At any given point of interest in time t, system availability is the probability of the system in one of the success states, $P_i(t)$. The simplest case for determining the steady state availability is a single system with both a constant failure rate, λ, and a constant repair rate, r. Assume that the system will be one of the two possible states; state 1 is operating and state 2 under repair or failed state. The basic concept of the state diagram, sometimes called the transition rate diagram, can be shown as in Figure 2.6 and 2.7. The general equation for n independent equipment in a series has an equipment availability, $A_i(t)$, and the system's availability is given by Equation 2.12 [1]:

$$A_S(t) = \prod_{i=1}^{n} A_i\,(t) \tag{2.12}$$

Similarly, the general equation for n independent equipment in parallel configuration has an equipment availability, $A_i(t)$. The system's availability is shown in Equation 2.13 [1].

$$A_S(t) = 1 - \prod_{i=1}^{n}(1 - A_i\,(t)) \tag{2.13}$$

2.4 Application of Proposed Methodology

The proposed methodology has many applications and can be used on any continuous process, as well as other production processes with some modifications to the methodology. In this Chapter, the proposed methodology is applied to a gas absorption process, where high availability is a must in order to safely and economically run the process. The unavailability of this unit will cause all downstream processes to halt. In order to apply the methodology in the most effective way, it is essential to review the functional details of the process to understand the operating nature of the process. It will help to understand the hazards and their consequences. Secondly, a knowledgeable team with strong exposure to the process and equipment is required. The foundational step is to identify the critical components that cause functional failure to the process unit to develop the model, functional block diagram and other steps as discussed in framework. The following Section shows the implementation of methodology explored in Figure 2.3.

2.4.1 Brief Description of Absorption Process

A gas sweetening unit is one of the major gas treatment units in a gas processing plant prior to other processes in the plant like liquefaction, fractionation, and gas separation. It mainly consists of acid gas removal from the gas stream. This unit primarily consists of absorption, regeneration and reclaiming Sections. In order to observe the proposed methodology, we will only focus on the absorption Section of the process. The simplified block diagram Figure 2.5 explains the functionality.

The absorption Section absorbs hydrogen sulphide and carbon dioxide. The regeneration Section mainly regenerates the solvent and sends stripped out lean acid gas to the sulfur recovery unit, subsequently; the regenerated solvent is circulated back into the absorption Section for natural gas sweetening process. Natural gas consists of mainly gaseous hydrocarbons, partly heavy hydrocarbon and around 1 to 2 percent of acidic gases like hydrogen sulfide and carbon dioxide and other sulphur compounds. Acidic gases are highly corrosive and will cause severe damage to cryogenic vessels during liquefaction process; therefore, it is necessary to remove these gases and contaminants before they reach the final stages of liquefaction. In the acid gas absorbers, hydrogen sulfide and carbon dioxide gases are absorbed completely in the solvent and sweet natural gas is routed to the gas drying Section and liquefaction units. The sour gas from the inlet receiving area enters in the reception Section where gas is preheated at optimal value to avoid condensation prior to introduction in the gas sweetening Section. The acid gases enter absorber column where H_2S, CO_2 and sulfur compounds are removed by counter current contact of the gases with a lean solvent in order to meet the required specification of sweet gas. Since the natural gas sweetening process is very critical in terms of operation and commitment of the LNG production, the availability of all the equipment remains under focus and operational integrity is monitored closely. For reliable processing of the gas sweetening unit, all static and rotating equipment are monitored closely for corrosions due to acidic streams, wall losses due to erosion caused by high velocities or turbulences. Rotating equipment are surveyed with their historical records and failure history. To estimate the availability, the above mentioned framework has been followed in the remaining Section.

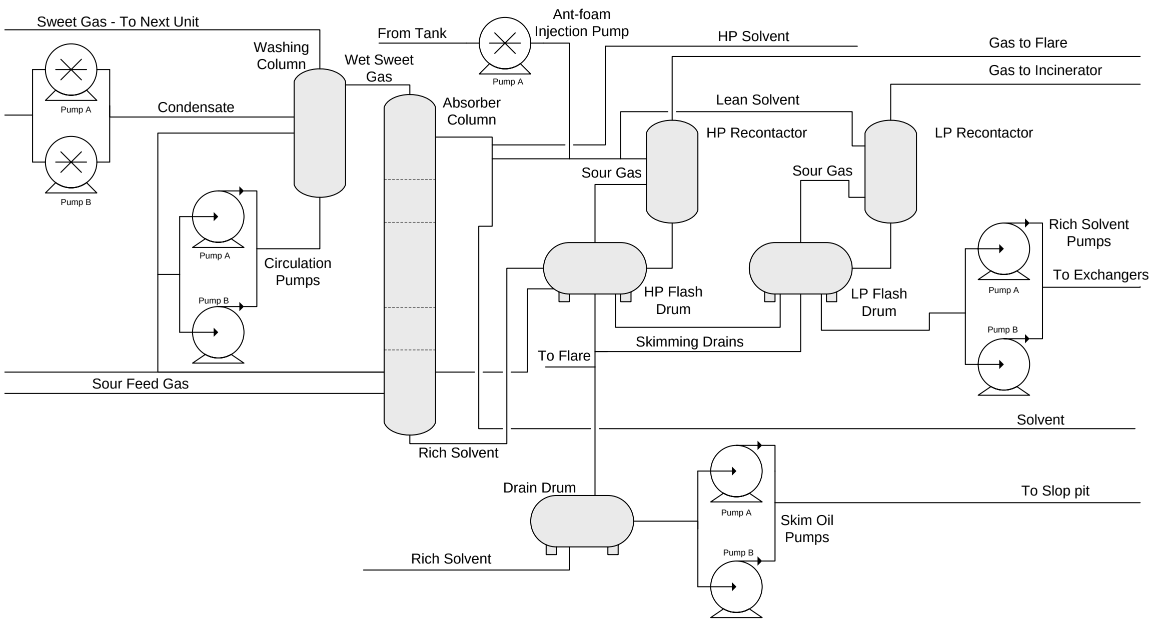

Figure 2.4: Simplified gas absorption process

2.4.2 Risk Assessment

As discussed earlier, risk assessment (RA) is a systematic approach in performing risk analysis to identify the failure probability and consequence of the failure due to exposure to hazards. The goal of RA is to evaluate the magnitude and probability of actual and potential harm or an actual event [20]. The main hazards in the processing industry are hydrocarbon, high pressure, high and low temperatures, and poisonous gases. The consequences can be due to any reason, i.e. equipment breakdown means lower MTBFs, operating beyond operating windows, higher MTTRs, gas release or human mistakes. This step is one of the foundations of the complete process. Companies have risk matrix and risk evaluation methods that can be used to identify critical equipment in a processing unit and sometimes information is already provided in computerized maintenance management system. Categorization of the equipment is carried out this step whereas; in next step, a simplified block diagram is developed with critical elements in the process. Usually the outcome of this process is a list of equipment with high, medium and low priority. The critical equipment can also be ranked using ranking numbering, sometime referred as the criticality number, i.e. if the consequence is extreme or 5 and the probability is frequent or 5, the product represents the risk or criticality, which is 25. It is recommended to use only critical equipment but other equipment based on the consequence can be included. Simply, risk is estimated based on the risk assessment matrix using Equation 2.1. In general, if the risk belongs to a safety consequence category, it takes precedence and is considered as critical. The following criterion is utilized to identify the critical equipment that can cause functional failure of the unit. In addition to usual risk criteria, we have introduced the reliability and maintainability consequence because they directly relate to the availability of the processing unit. Individual categories can be explained as follows:

Table 2.1: Safety Health and Environment

Ranking	Description (SHE)
Extreme (5)	Fatalities, sever environmental impact
High (4)	Permanent disabilities, major environmental impact
Medium (3)	Major injury, local environmental impact
Minor (2)	Minor Injury, plant-wide environmental impact
Negligible (1)	First Aid , no environmental impact

Table 2.2: Economics, Reliability and Maintainability

Ranking	Description (Economics)	Description (MTBF)	Description (MTTR)
Extreme (5)	Downtime > X_3 hrs	MTBF < Y hrs	MTTR > Z_3 hrs
High (4)	Downtime > X_2 < X_3 hrs	MTBF > Y < Y_1 hrs	MTTR > Z_2 < Z_3 hrs
Medium (3)	Downtime > X_1 < X_2 hrs	MTBF > Y_1 < Y_2 hrs	MTTR > Z_1 < Z_2 hrs
Minor (2)	Downtime > X < X_1 hrs	MTBF > Y_2 < Y_3 hrs	MTTR > Z < Z_1 hrs
Negligible (1)	Downtime < X hrs	MTBF > Y_3 hrs	MTTR < Z hrs

Parameter ranges X, Y and Z in Table 2.2 to rank the consequence are dependent upon the company business and business guidelines. After the identification of the critical equipment, the next step is to develop a functional block diagram based on identified critical equipment, as shown in Figure 2.5. This methodology can be used to include medium critical equipment in the block diagram depending upon the consequences but it will increase the size of the model.

2.4.3 Simplified Functional Block Diagram

As discussed earlier, we have selected this system due to the criticality of its application; presence of poisonous gases, safety impacts on plant and society in case of unwanted breakdown, including financial consequences. We have presented the unit in small systems to manage it properly for calculation purposes. This unit consists of stationary assets and rotary assets as well as piping and valves, as is the case in other oil and gas processing units. We have developed a block diagram to better understand the system view of the rotating machinery and static assets in the system. This includes pumps, motors, valves, vessel piping, and other equipment. The block diagram shows the redundancy level and criticality of the equipment.

The pumping system consists of a pump and motor as a single functional location but the failure rates are added to represent the real picture. The pump and motor are considered as a system in order to calculate the required parameter and are later utilized in the comprehensive model. In this step, we can also include a well-judged value of the failure rates of other critical systems to bring results closer to the real case. All the piping is considered a system and the applicable failure modes have been used to determine the piping failure rate, and similar is true for valves. There may not be any impact on availability of the system but reliability may be different if there is a failure in the redundant system. The individual capacities available are shown in the block diagram in Figure 2.5.

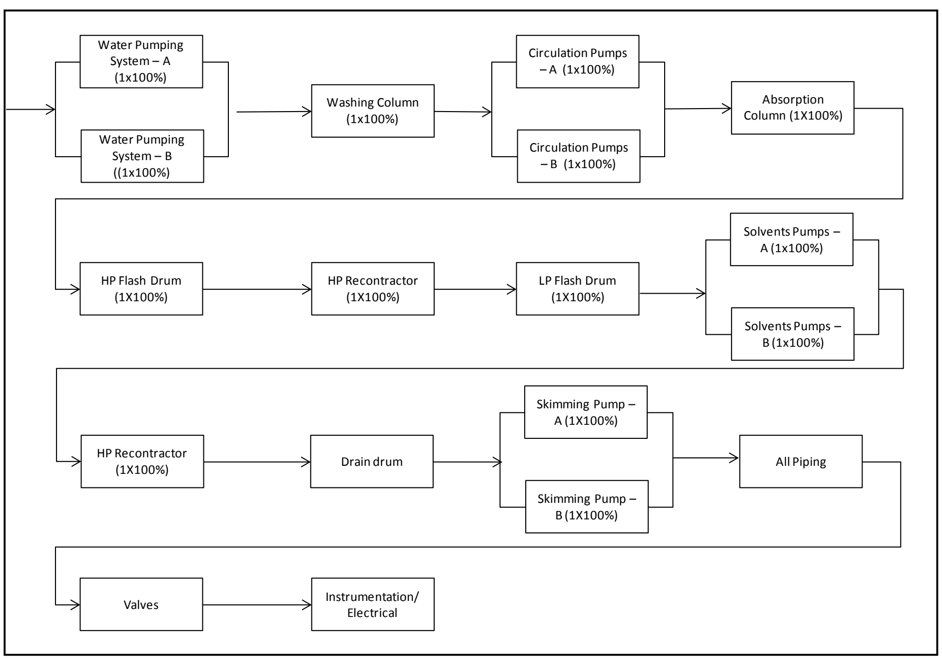

Figure 2.5: Functional block diagram

2.4.4 Failure Data for Analysis

Failure data is a key to the proposed methodology or even for any statistical analysis. Equipment's historical maintenance and repair data availability and quality is an industry concern, which discouraged us from using the data directly from maintenance history database. Estimations were developed with the help of engineers and technicians in order to use the best data. Inconsistency in the available data drove us to get help from OREDA. OREDA data was not even directly utilized in the analysis but data was sorted and compiled. The applicable realistic failure modes from the field were identified to estimate failure rate and repair rates. To effectively model the process and outcome, the real data and OREDA was utilized together. OREDA database has many failure modes for any equipment but all are not applicable to every facility. Instead of using all failure modes, only applicable failure modes were used to estimate the mean failure rate and repair rates. As an example, OREDA estimates mean time between failures for a pump which is 4 years based on all failure modes but some of the failure modes are not experienced as per the failure history. Those failure modes have been taken out to estimate the realistic mean time between failures. Once taken out the failure modes, mean time between failures improves to 5 years which is best representative of our case. Active repair rates [22] were used in the calculation, which refers to the actual time spent on the repair operation rather than the total downtime or man-hours.

Failure is classified when the equipment is not working or degraded, such as small leak or passing, when the system is partially available or functional. In vessels, columns and piping, leaks have taken as a degraded and failed state. Both motor and pump are considered as pumping system in order to avoid confusion because the systems will not work without one another and will represent the real scenario. All the valves and piping in the process have been taken as a sub-system and corresponding failure rate and repair rates have been used to simplify the process. The inclusion of piping and other sub-systems is also very critical as they experience failures as well to estimate the availability.

Data was used with extreme care, and consideration was given to feasible and experienced failure modes to estimate the failure rates. In case of rotating machines, calendar time was used in active systems and operational data was used in standby systems to be more precise in the calculations. The static equipment data was collected based on the calendar time, as they were all functional all the time. Availability of the instrumentation and electrical system is usually very high due to its inherent design so the system is not selected as part of the process, but the control valves and other emergency shutdown valves are included in the system. Table 2.3 contains the rotating equipment data, including both active system failure rates and repair rates as well the standby system rates. Table 2.4 has all static failure rates and repair rates.

Table 2.3: Rotating Equipment

Code	Description	Active Failure Rate	S/B Failure Rate (/Hr)	Repair Rate (/Hr)	S/B Repair Rate (/Hr)
SR_1	Pumping System	490.7E-06	13.65	33.0	14.0
SR_2	Circulation System	322.4E-06	5.71	28.9	33.7
SR_3	Sol. Pumping System	168.9E-06	13.92	7.5	2.5
SR_4	A-Foam Inj. System	1.4E-03	-	6.0	-
SR_5	Oil Pumping System	1.2E-03	14.9	8.5	7.8

Table 2.4: Static Equipment

Code	Description	Failure Rate (/Hr)	Degraded Failure Rate (/Hrs)	Repair Rate (/Hrs)	Degraded Repair Rate (/Hrs)
SS_1	Washing Column	2.8E-05	2.01E-04	14.0	51.4
SS_2	Absorbing Column	5.7E-05	3.4E-04	75.1	24.3
SS_3	HP Drum	3.4E-05	5.4E-06	4.8	8.5
SS_4	HP Column	9.1E-05	2.8E-05	27.1	13.1
SS_5	LP Drum	3.4E-05	5.45E-06	449.6	17.0
SS_6	LP Column	9.1E-05	2.8E-05	27.1	13.1
SS_7	Drain Drum	2.5E-05	2.8E-05	29.8	8.5
SS_8	Piping	4.4E-05	-	2.0	-
SS_9	Valves	8.5E-06	8.0E-06	6.79	9.1

2.4.5 Risk based Availability Markov Model (RBAMM)

RBAMM proposed in this Chapter has been applied to validate the applicability of the model in a real plant situation. It is very difficult to calculate the availability of a unit with a higher number of equipment based on the individual equipment failure rate. That is why it is often modeled using operating parameters like production loss, name plate capacity and sustainable capacity to estimate operation availability and reliability. The outcome is usually based on the production output rather than on equipment failure rate. Selection of the unit for this research is based on risk assessment. To develop the model of the system under study, system is broken down into many small manageable systems of the same function, as can be seen in Figure 2.5. Most of the operating units are modeled using a Markov state process. One of the state diagrams has shown below in Figure 2.6. It is a very cumbersome process to model the complete system and use real failure rates of equipment where the unit consists of thousands of functional locations. In order to make it simpler, block diagram Figure 2.5 was developed using a risk matrix. Critical equipment has been chosen based on the RAM to simplify the system for availability estimation. In addition to using simplified block diagram, we proposed to calculate the availability of the independent sub-systems and later Equation 2.3 to solve for the complete system. In the given critical system, if we choose to model the system as a whole with only 2 states of 14 sub-systems, the total state equations would be 16384. The size of the model will exponentially go even higher if we opt to apply the methodology on the complete system.

The model developed has three real plant conditions; they are: 1. all functional, 2. degraded running and, finally, 3. failed state. The block diagram has been broken down into smaller entities based on the functionality of the equipment. A real plant scenario has been used to model the system. Mainly, the systems have been broken down into five essential systems, i.e. static equipment, rotating equipment, piping, valve systems and others mainly consisting of electrical. Though the pumping system drivers are mainly electrical motors, due to the functional reasons they have been considered as one system because if the motor or pump failed the output is a failed state for the system. The Markov methodology has been used to develop state models, which provide an opportunity to model realistic operating scenarios, like operational, failure, and degraded state. A real plant case has been used in modeling the real conditions. A general model has been discussed in the beginning; specific details are shown below. Complete system has been broken down in the following sub systems as shown in Table 2.5. In this approach, once the availabilities of the subsystems are calculated, the block diagram will be used to calculate the total availability of the system. The advantage of separately calculating the static, rotating and other equipment will provide the flexibility to identify if any one of the systems is a bottleneck and requires more focused work to improve availability and reliability. There are many different operating scenarios that can be easily modeled using a Markov process. In this system, two different systems available were commonly used during the Markov modeling process. Pumping systems with redundancies were modeled using the state diagram shown in Figure 2.6, and a non-redundant system i.e. Absorber Column, is modeled with three operating states as in Figure 2.7. In this model, state 1 represents the equipment is functional as designed and state 2 reflects the equipment is working but not meeting the functional requirements. For example, valve is passing and process is still functional with degraded performance. State 3 represents the complete failure where the repair is inevitable. At state 3, once the equipment is repaired the system goes back to state 1, and from this state system cannot go back to degraded state. Once the system is fixed, it will only go to its initial state 1.

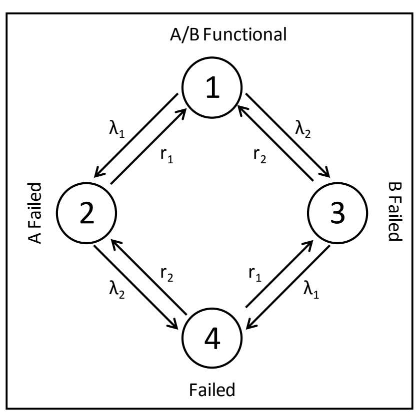

Figure 2.6: State diagram of two pieces of equipment in parallel with failure in standby

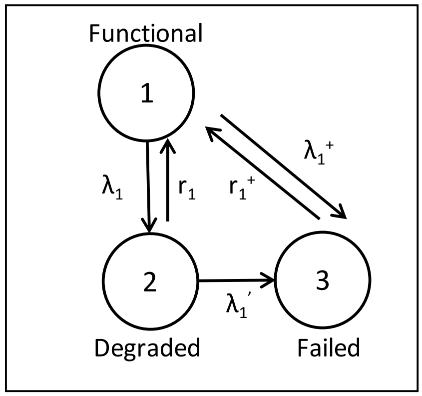

Figure 2.7: State diagram of a three state degraded system with repair

The set of steady state equations using Equation 2.10 to calculate probabilities of system shown in Figure 2.6 are:

$$\text{State 1: } (\lambda_1 + \lambda_2)P_1 = r_1 P_2 + r_2 P_3 \quad (2.14)$$

$$\text{State 2: } (\lambda_2 + r_1)P_2 = \lambda_1 P_1 + r_2 P_4 \quad (2.15)$$

$$\text{State 3: } (\lambda_1 + r_2)P_3 = \lambda_2 P_1 + r_1 P_4 \quad (2.16)$$

$$\text{State 4: } (r_2 + r_1)P_4 = \lambda_2 P_2 + \lambda_1 P_3 \quad (2.17)$$

$$P_1 + P_2 + P_3 + P_4 = 1 \quad (2.18)$$

In general, availability of a system can be written as [4]:

$$A_S = \sum_{\substack{all\ sucess \\ sates\ i}}^{.} P_i \quad (2.19)$$

Using Equation 2.19, the availability of the system shown in Figure 2.6. can be written as:

$$A(s) = P_1 + P_2 + P_3 \quad (2.20)$$

Similarly, three state systems and other system equations can be developed to calculate a system's availability. Providing all the static systems in series, Equation 2.22 can be used to determine the overall availability of the static system and similar process can be done for rotating equipment. The overall unit availability will be calculated using Equation 2.24.

$$A_{SR} = \prod_{n=1}^{j} ASR_n \tag{2.21}$$

$$A_{SS} = \prod_{n=1}^{j} ASS_n \tag{2.22}$$

$$A(Unit) = \prod \ (Sub\ systems\ in\ series) \tag{2.23}$$

$$A_U = \prod_{i=1}^{n} A_i \tag{2.24}$$

where, A_U = Unit Availability, A_{SR} = Availability – Rotating System, A_{SS} = Availability – Static System and i = individual sub systems.

2.5 Numerical Analysis and Results

Certain constraints are important to understand prior to interpreting results. The most important is that the data used in the analysis is a combination of real process data with OREDA. Applicable failure modes were identified and used to calculate MTBF and MTTR for individual systems. The standby system failure rate is also calculated using the historical data and OREDA. This aids us in using our real plant data to reduce bias in the results. Proposed methodology helps to calculate the availability of the individual sub system and can be used to identify bottleneck in the system. Table 2.5 shows the availability of the individual subsystem whereas Table 2.6 shows the availabilities of static and rotating as well the unit availability. In the existing approach to estimate availability at facility, it is very difficult to calculate the individual availability of the subsystems, but the proposed methodology has the flexibility to estimate all availabilities.

Table 2.5: Individual Availabilities of Subsystems

Code	Description	Availability
SR_1	Water Pumping System	0.945
SR_2	Water Circulation System	0.998
SR_3	Solvent Pumping System	0.909
SR_4	Anti-Foam Inj. System	0.995
SR_5	Skim Oil Pumping System	0.768
SS_1	Water Washing Column	0.957
SS_2	Acid Gas Absorbing	0.968
SS_3	High Pressure Drum	0.999
SS_4	High Pressure Column	0.947
SS_5	Low Pressure Drum	0.999
SS_6	Low Pressure Column	0.947
SS_7	Drain Drum	0.926
SS_8	All Piping	0.999
SS9	Valves	0.999

Steady states equations were developed using Equation 2.1 and solved by using Excel to calculate probabilities of certain states to estimate the availability of subsystems. Once the availabilities have been judged, Equation 2.11 is used to determine the availability of the complete unit, which is the product of static equipment and rotating equipment availabilities. The difference in the existing methodology and the proposed methodology is almost very small, as the results differ by only half a percent.

Table 2.6: Comparison of Availabilities

Description	Existing Approach	Proposed Approach	% Difference
Static Equipment		99.89	-
Rotating Equipment		99.13	-
Overall Unit	99.50	99.02	0.5

The suggested approach provides certain benefits over the existing methodology and is discussed in Section 2.5. It is difficult to compare the availability at unit or subsystem levels because data at a subsystem level is not available in current practices. Overall, availability is comparable and the proposed methodology results are promising; the difference in results can be explained by the data estimation and other engineering judgments during the process. Figure 2.8 graphically shows that the proposed methodology provides flexibility to estimate the availability of subsystems in a processing unit.

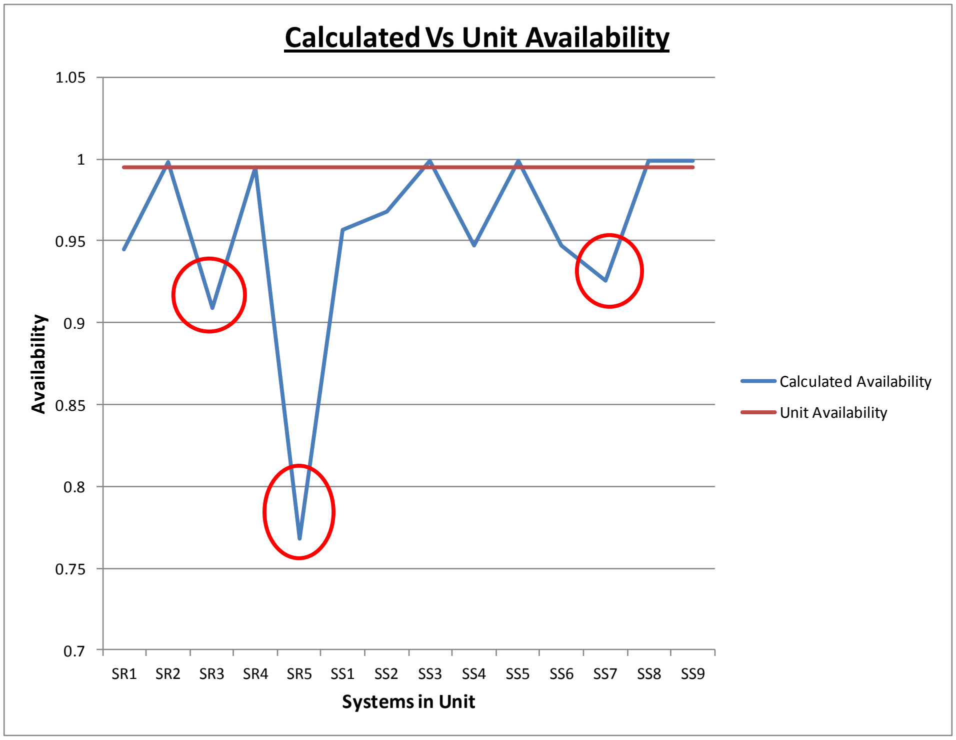

Figure 2.8: Graphical comparison of availabilities

Prior to the proposed methodology, unit availability is a value, which is 99.5%, and represented by a straight line. It was difficult to estimate subsystem availabilities quickly to identify the bottleneck and area of concern. With the proposed scheme, subsystems availabilities are estimated from the start, which makes it easier to identify areas of concern and efficient utilization of resources.

2.5.1 Advantages and Limitations of Proposed Methodology

The proposed methodology has shown very promising results and comparable to existing availability of the processing unit with other important benefits. The advantages mentioned below provide better control and understanding of the processing unit. Some supremacy of the risk-based proposed methodology has been proven and is discussed below.

a. Efficient planning tool; allocation of resources as the individual asset system availabilities are available to identify poor performers as shown in Figure 2.8. Poor performing systems can easily be identified and detailed analysis can be performed.
b. Identification of real plant critical equipment that affect the availability of the plant.
c. Prioritization of the maintenance work based on criticality classification.
d. Risk assessments performed can be used in reliability centered maintenance activities.
e. Long term planning, once plant model is developed; quick identification of bad actors.
f. Initiative to enhance the maintenance history data program.
g. Better spare parts and maintenance planning to reduce MTTR.
h. Effective tool to optimize turn around and inspection shutdown.

The proposed framework is flexible and easy to use when using the step by step process discussed in Section 2.3. Proper attention must be given to step by step execution while performing studies using this approach. The risk matrix used in risk-based assessment must reflect the company risk criteria rather than individual departmental criteria. It is an experience that different departments have their own risk matrices to prioritize their work. Use of the matrix ensures that the experienced personnel are involved in performing risk assessment with good understanding of the system and its failure consequences. Failure history data must be used with care and questionable data must be scrutinized or normalized properly. The state models must consider all the experienced failed states to obtain more realistic results.

2.6 Conclusion

Many methods have been discussed in the literature review to estimate the availability of independent systems, but efforts toward the estimation of processing facilities, like gas plants or refineries, were found to be limited. The proposed methodology establishes an efficient and effective way to manage assets, as well as estimate and improve availability. The suggested approach to estimate the availability using RBAMM of a processing unit is unique and has shown promising results compared to existing methodology. The exclusivity of this proposal is the risk-based approach, which tends to alleviate the data scarcity situation by selecting the critical equipment in a unit and utilizing the failure databases smartly.

The method discussed addresses a real field issue and provides a solution to the issue with a high level of confidence. Data was reviewed and adjusted based on engineering judgment in conjunction with OREDA to make it suitable for use. This methodology provides an opportunity to identify subsystem availability, which helps us identify the true bottleneck in a processing unit. The proposed research engages the issue of calculating the availability of a continuous operating plant. The model is validated on the real configuration of the plant and the real operating scenarios so that the results will be realistic. This research also highlights the need and importance of good quality maintenance history and effective utilization of the existing data to perform similar studies with more confidence.

A risk-based methodology can be extended to develop a computer application using the proposed approach for operating plant use. It is an optimal risk based solution for users to efficiently utilize resources and achieve better results with less operating cost. The effective utilization of the suggested method will help reduce cost and improve plant reliability and availability.

CHAPTER 3

IMPROVING AVAILABILITY USING A RISK-BASED FAILURE ASSESSMENT APPROACH [3]

Abstract

A structured risk-based failure assessment (RBFA) approach is presented, which provides a complete solution to avoid repeated and potential failures to improve overall plant safety and availability. Technological advancements and high product demand have encouraged designers to design mega-capacity systems to enhance system utilization and improve revenues. These benefits make the systems more complex and so prone to failure.

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[3] *This Chapter is based on the published work in a peer-reviewed journal. Qadeer Ahmed, Faisal Khan, Salim Ahmed (2014), "Improving safety and availability of complex systems using a risk-based failure assessment approach," Journal of Loss Prevention in the Process Industries, Volume 32, November 2014, pages 218-229. To minimize the duplication, all the references are listed in the reference list. The contribution of the authors is presented in Section titled, "Co-authorship Statement".*

In general, despite the elaborately planned maintenance and monitoring activities, equipment still fails. In reality, it is an overwhelming task to address all the failures due to limited resources and time constraints. This leads to substandard and poor quality failure assessments, which cause repeated failures. To address this common industry concern, a four phase RBFA framework is proposed, which is not limited to the identification of root cause(s) but also includes all the other actions essential for a successful assessment. The four phases include the plan phase, the assessment phase, the analysis phase, and the implementation-tracking phase. These phases cover identification of failure and failure analysis; root cause(s) along with corrective actions are mooted, prioritized, and monitored for implementation. In this Chapter, the applicability and advantages of the proposed approach are examined through two real case studies pertaining to bearing failure and drive coupling failure. Significant improvements have been experienced in the mean time between failure (MTBF) and system availability for both the cases.

3.1 Introduction

In a processing facility, equipment and systems are anticipated to perform their function safely and reliably to meet production requirements. Despite the best maintenance and operating strategies, systems and equipment fail. These failures must be analyzed properly to identify the root cause(s) and implement corrective actions to avoid repetition. Repeated failures are very common where the failure assessment is done poorly and corrective actions are implemented without proper validation of the root cause(s). In a study [1], the failure history shows that the fuel oil pump experienced 14 failures during an operating life of 10 years. In another study of repeat failures, the authors mentioned that 18 events of compressor failures occurred during the last 12 years. These examples highlight the fact that failure investigations are either not handled properly or corrective actions are not implemented properly. A thorough and structured investigation process is therefore needed to avoid the general problem of repeated failures [2].

Failure is defined as an *"inability to perform the intended function,"* whereas a fault is "*an abnormal condition or defect at the component, equipment or subsystem level, which may lead to a failure"* [3-4]. Risk-based failure analysis in this work is defined as, *"a structured process that discovers root cause(s) — physical, human, or latent of an incident (failure or fault) and addresses these causes with corrective actions to improve the availability and safety of the workplace."* Failure and availability are two sides of a coin; reduction in equipment failures greatly improves the availability of the system and vice versa. Failure can be eliminated or reduced by effective maintenance, adequate operation, proper design, and other parameters. In case of a failure, proper failure investigation is important to identify and eliminate the root cause(s). Availability improvement is neither one size fits all nor a piece of technology or software solution; it is a strategic objective to be met. Therefore, all the factors affecting availability are essentially considered with their importance. An appropriate combination of assessment approach, tools, and technologies is vital to reduce failures but the list also contains skills and good planning to achieve this goal. Availability suggests the readiness of the system when required. Many factors affect the readiness of the system, including planned downtime for preventive maintenance, unplanned breakdowns, and availability of spares. Availability can be significantly improved by reducing the equipment downtime by either addressing reliability or maintainability [5]. A major factor of poor availability is repeat failure or recurrence of a failure, which can be reduced by a structured and smarter root cause analysis approach, with the assurance that the corrective actions have been implemented. Analyzing failures correctly improves the failure rate, which means minimization of downtime and repair time, ensuring better mean time between failures (MTBF) and mean time to repair (MTTR) as represented in Equations 3.1 and 3.2.

$$Availability\ (A) = \frac{Uptime}{Uptime + Downtime} \tag{3.1}$$

Availability can also be written as,

$$Availability\ (A) = \frac{MTBF}{MTBF + MTTR} \tag{3.2}$$

where, MTBF = Mean Time Between Failures and MTTR = Mean Time to Repairs

Equation 3.2 can also be expresses as,

$$Availability\ (A) = \frac{\mu}{(\lambda + \mu)} \tag{3.3}$$

where, λ = Failure Rate and μ=Repair Rate

As an illustration, an improvement in MTBF by 90 days and repair time by 5 days in a year, results in an overall availability improvement of 2.5%. Highly structured failure analysis approaches are required to achieve such objectives in asset intensive industries like gas processing, nuclear, and aerospace.

Failure analysis is a multifaceted and challenging task but with a structured methodology, knowledgeable and skilled team, the real root cause(s) can be efficiently identified. The identification of the root cause(s) does not lead to the conclusion of the objective because the real solution is to develop corrective actions and to implement them to avoid repeat failures. A structured approach is a way to analyze failures because unstructured processes only support opinions and are unable to produce lasting results. As a result, supporting a structured approach in problem solving is highly desirable [6]. Failure consequences drive the classification of the failure investigation. Classification is required so that the investigation can be performed based on the criticality of the failure. Failure investigation can be classified by the importance and criticality of a failure, which derives the need of a detailed analysis [7]. Based on the risk consequences, failure analysis is categorized as high, medium, or low. Brief investigations are performed on non-critical failures whereas a detailed analysis is required on critical failures along with effective management of the corrective actions. Investigations limited to only identifying the reason of a material failure and restricted to a component analysis are usually classified as component failure analysis and do not address the system issues. For example, a bearing analysis is performed and the result indicates a lack of lubrication but the reasons of the lack of lubrication are not discussed. Root cause(s) investigation covers other causes, i.e., human causes but does not explore the latent causes. Root cause and failure analysis cover all three areas of cause identification as discussed above but still the other parts of the complete process are not included. In this research, a complete failure analysis process, risk-based failure assessment, is proposed that starts from a failure or fault event, to identification of root cause(s), to implementation of recommendations and extends up to the effectiveness of corrective actions. In this Chapter, a four-phase RBFA framework is proposed, which is not limited to the identification of root cause(s) only but also includes all the other actions essential for a successful assessment. The applicability and advantages of the proposed RBFA approach are examined through two case studies pertaining to bearing failure and drive coupling failure.

The remainder of the Chapter is organized as follows: Section 3.2 explores the research work done in this area. Section 3.3 discusses the risk-based failure assessment framework. Section 3.4 presents two case studies to observe the application of proposed approach and the results. Section 3.5 discusses the critical success factor of the proposed methodology. At the end, in Section 3.6, a conclusion and contributions are discussed.

3.2 Background Study

Failures and faults are the most undesirable events that adversely affect the availability of an operating facility. To avoid such events, engineers do their best to effectively operate and maintain the system. Many tools such as condition monitoring and process monitoring are available to proactively predict and analyze such unwanted events but failures still exist. Along with other efforts, proper failure analysis is the key to address these unwanted events by identifying the real root cause(s) along with developing and implementing corrective actions.

In industry, many tools are available to carry out root cause analysis of a failure. Some of the common tools employed are 5 Whys, Fault Tree Analysis, Ishikawa Diagrams (commonly known as Fishbone Diagrams), and Failure Mode and Effects Analysis (FMEA). Use of these tools is questionable as witnessed by many recurrences and repeated failures. In one study, the performance of three popular root-cause analysis tools namely, Cause-and-Effect Diagram, the Interrelationship Diagram, and the Current Reality Tree were analyzed [8]. It was found that these tools have the capacity to find root causes with varying degrees of accuracy and quality due to their individual unique characteristics and application constraints. In the literature, different methodologies have been used to estimate the availability ranging from fault detection, reliability block diagrams, FMEA, fault tree analysis, and so forth [2, 9, 10, and 11]. A great opportunity exists in addressing system availability using a risk-based systematic approach, which is proposed in this work. Production pressure and operating constraints necessitate that investigations must be completed quickly. Quick complex failure analysis contributes to repeated failures and wrong root cause(s) due to limited focus on identification of the real root cause(s), accepting or rejecting all failure possibilities, and bypassing a structured failure investigation. The other common problem is the lack of focus on the implementation of corrective actions, which is one of the major contributors to repeated failures. In this work, there is more focus on the "operate and maintain phase," which is truly the longest phase in the life-cycle of equipment as shown in Figure 3.1. The proposed model can be used effectively to assess potential failures or conditions in design and construction.

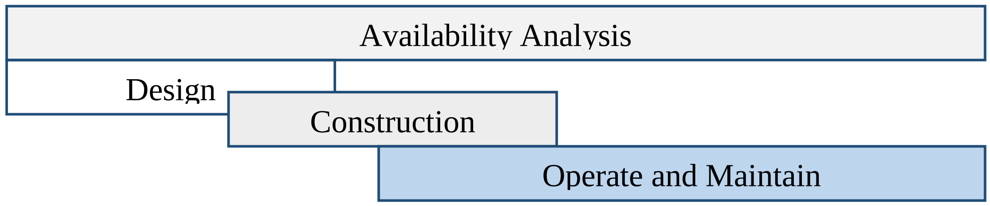

Figure 3.1: Availability – operate and maintain

Fault Tree Analysis (FTA) is a top-down failure investigation approach to perform studies to improve the availability, reliability, and safety of the systems. The approach discussed in [12] does not provide a holistic solution to address repeated failures and availability. In another work, plant safety and availability improvement is suggested using reliability engineering tools [13]. In this technological era, signal processing has been proven to be very effective in performing fault diagnostics and prognostics to improve availability and maintainability of complex operating systems. The Kalman filter based ensemble approach is used to predict the remaining useful life of a turbine blade creep degradation process [14]. Stochastic models are great in predicting the useful life of equipment, but they lack an approach for addressing real plant failure causes. Prognostic and health management is a research area that may provide a solution and guidance to industry to maintain the availability of the systems, safety, and economics of the operating facilities. A technical framework of equipment health management based on six key elements during the design stage for complex mechanical systems is proposed [15]. A comparison between the traditional and proposed health management framework is performed along with validation using case studies, which works well proactively to avoid failure rather than assess failures. In an another effort, a novel and highly sophisticated layered dynamic hybrid fault modeling and extended evolutionary game theory is proposed for reliability, survivability, and fault tolerance analysis [16]. Due to the complexity and sophistication, the authors have recommended developing software to implement such a sophisticated model for ensuring the integrity of the modeling technique. Complex and highly advanced tools sometime hinder efforts and make it difficult to analyze failure effectively. To evaluate the consequences of a certain fault or failure, risk is an important aspect to evaluate in complex systems. To study the relationship between risk, availability and its consequences in certain scenarios, a risk-based availability analysis model is presented [17]. The proposed model helps in maximizing reliability and improving the maintainability of systems, which enhances availability as shown in Equation 3.2. Avoidance of repeated failures improves reliability and availability, which can be easily achieved by proper failure investigation and implementation of the recommendations of this study. As proposed in [18], a risk-based availability model is used to optimize maintenance strategies. In this work, imperfect maintenance has been discussed in context with equipment availability. Virtual age models of imperfect maintenance are used to estimate the availability of the equipment. An availability model of repairable equipment based on virtual age is defined and, by using a simulation availability function, availability is estimated. Imperfect maintenance is also a source of failure and requires proper attention to improve maintenance. In another study, a model for fault detection and availability in complex services is investigated [19]. A realistic reliability model to study the asset allocation problem to obtain the desired level of availability is presented. The model is validated using a real case of a multimedia communication service.

As discussed above, many different techniques and methodologies are presented to estimate availability but limited work seems to have been done to address availability using proper failure analysis. In this Chapter, a risk-based failure analysis approach is proposed, which addresses the issue of an equipment failure, repeat and potential failures to enhance availability. This approach is based on a structured risk-based process, which helps in streamlining the process of identifying the real root cause(s), and to develop and prioritize corrective actions for implementation.

3.3 Risk-Based Failure Assessment (RBFA) Framework

Reducing risk and improving availability are the prime objectives of any processing facility. Risk can greatly be reduced by avoiding repeated and potential failures. A structured and robust risk-based failure assessment process is a result-oriented tool to address this issue. Failure assessment is one of the basic availability enhancement tools and can be performed in formal and informal setups [20]. To effectively use the assessment process, the classification of failure is required. It is extremely important to conduct the assessment either formally or informally to ensure the optimal and efficient use of the resources. The classification of a failure drives the criticality of the failure and suggests the level of failure investigation required. In certain cases, a simple process is an effective way to perform failure assessment and on the other hand, in critical cases, a thorough investigation with irrefutable evidences and a knowledgeable team has to be conducted to uncover the real root cause(s). An RBFA approach presented covers the complete process of failure assessment and enables us to use the optimal way of performing failure investigations. The proposed assessment process does not only cover the failure analysis and identifies the root cause (s) but it also provides a complete business process from identification, resolution to the avoidance of repeat failures. In complex plants and machines, failures have significant consequences and the equipment can fail in many ways, which requires the active involvement of knowledgeable personnel in the investigation process. The RBFA approach suggests performing failure assessment based on its criticality and the consequences of a failure. The risk-based philosophy helps in addressing the critical failures as formal and the non-critical ones as informal, which ultimately help organizations to allocate the right resources to high risk events. Proper investigation of all incidents and identification of the real root cause (s) is essential to avoid them in future; hence helping improve availability. The complete RBFA process has been divided into four phases and nine steps within the phases to elaborate the proposed methodology. The four phases and their steps are discussed below and are shown in Figure 3.2. The complete methodology of RBFA and recommendation management is discussed in Figure 3.3.

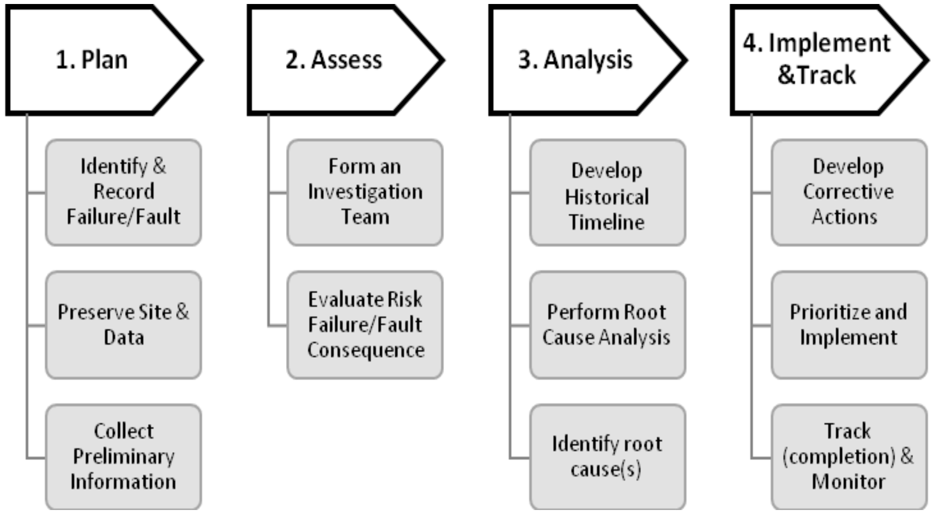

Figure 3.2: Four phases – risk-based failure assessment

3.1.1 Plan Phase

The planning phase is the most important phase in the proposed RBFA approach. Proper planning helps in understanding and defining the scope of the investigation. This phase provides the opportunity to have a first-hand feel and sets the stage for what to do and how to do it. This phase mainly covers the identification of an incident (failure) or potential incident (fault), and the collection of preliminary information. This phase provides the foundation upon which the remaining phases can be built. It has a significant impact on the complete approach. The three steps in this phase are as follows:

3.1.1.1 Identify and Record Failure/Fault

The first step in this phase is to identify and record an unwanted event i.e., a failure or a fault. The incident must be recorded in the maintenance management system or any other designated system with the basic failure information such as failure description, time, equipment number, and consequences of the failure. In order to develop a formal system, a separate platform is introduced and interfaced with asset performance management and asset maintenance management system [21]. The system facilitates the investigation process for proper execution and control.

3.1.1.2 Preserve Site and Data

The second step in this phase is to preserve the failure site and basic data. This step is critical in the investigation because it is in this step that the failed equipment is thoroughly observed, data is collected, pictures are taken for future reference and shared with the team during formal investigation. Failure assessment quality is dependent on the quality of the information. Therefore, the focus must be given to the right information from trustworthy sources.

3.1.1.3 Collect Preliminary Information

Good quality, realistic information is the core of an effective investigation process. During the planning phase, the preliminary and basic data must be collected prior to moving forward to the assessment phase. Preliminary data includes, but not limited to, equipment history, process flow diagrams, operating conditions, and process instrumentation diagrams. It may include interviews for the operation and maintenance to collect all the basic information.

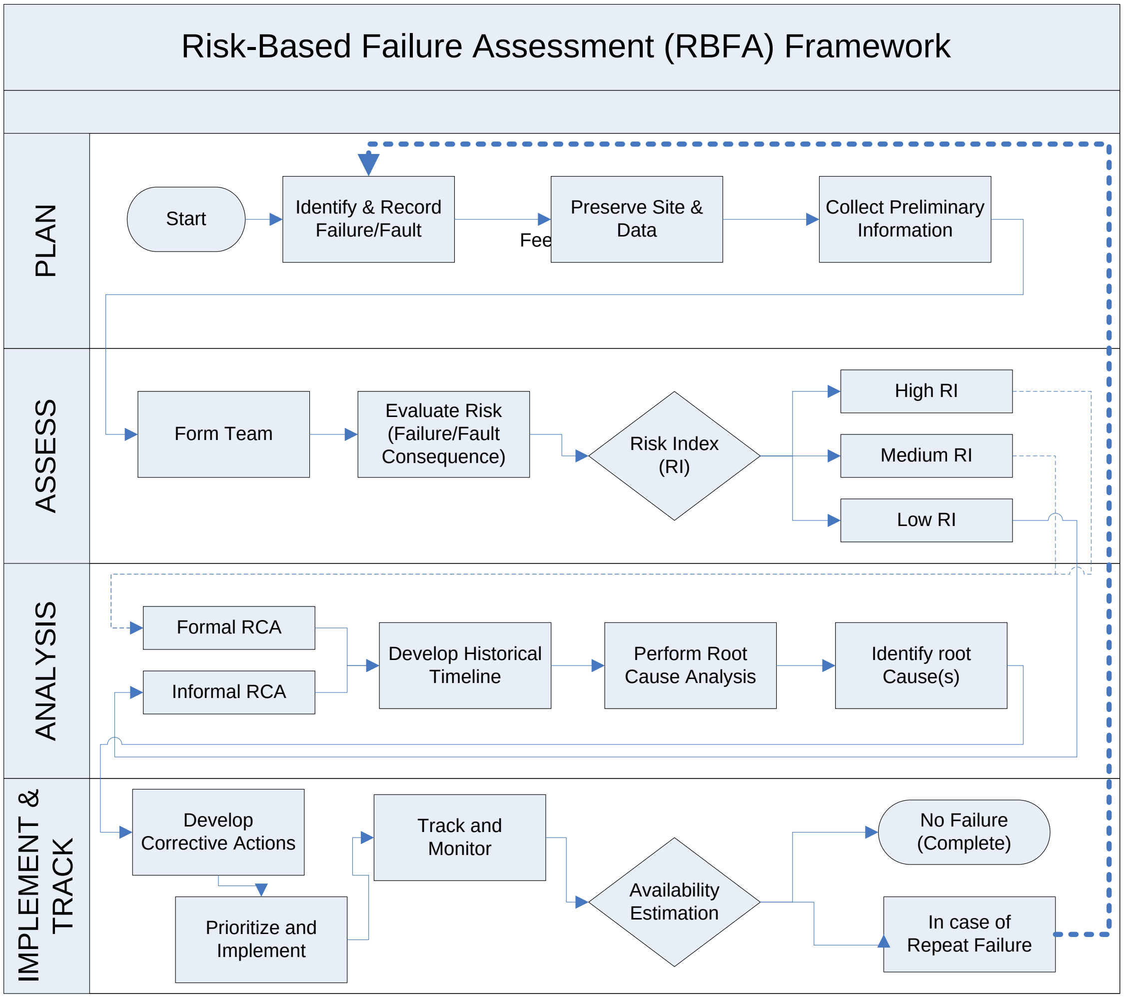

Figure 3.3: Proposed RCFA framework

3.1.2 Assessment Phase

In this phase, based on the collected information, a decision is made about the level of failure investigation that is required. Information is interrelated among the phases that make all the phases critical to each other. The input to the assessment phase mainly comes from the plan phase and other sources. Many investigations fail due to improper assessment of the failure. The personnel assigned to the investigation will review the planning phase information and make a decision about the personnel needed to be involved to assess the situation and be able to perform the criticality assessment.

3.1.2.1 Form an Investigation Team

Formation of an investigation team is a critical step in performing a thorough and formal investigation. Quality of the outcome also depends upon the involvement of subject matter experts in the related area. Successful investigation is only possible by choosing the right, responsible, autonomous and accountable team.

3.1.2.2 Evaluate Risk due to Failure or Fault Consequence

The failure risk assessment step is to evaluate the consequences of the failure, its impact on business, safety and health and the availability of the system. This assessment is a quantitative measure and is represented by a term, *"Risk Index (RI)"*. This assessment drives the level of the failure analysis effort, such as an investigation should be done informally or formally. Informal investigation is done by a small group of people following the same approach whereas the formal investigation is done by a structured group with a charter and a formal facilitator to conduct the assessment.

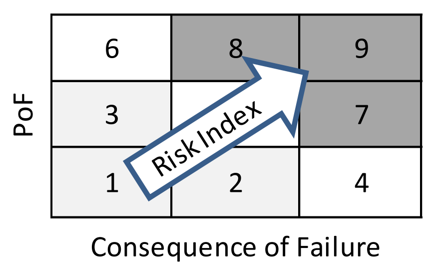

Figure 3.4: Risk assessment matrix

Assessment criteria should not be very stringent or shallow but should strike a balance among the consequences. The team should be able to easily use it to come to the conclusion. A 3x3 level risk matrix is sufficient for the purpose of failure classification to perform failure assessment. The outcome of the matrix can be qualitative in terms of low, medium or high as shown in Figure 3.4 or it can be quantitative in terms of Risk Index (RI) to assign a level of assessment and Equation 3.4 can be used for this purpose.

$$Risk\ Index = Probability\ of\ Failure\ (PoF)\ \times Consequences \tag{3.4}$$

For risk assessment,

$$Risk\ Index = PoF\ \times (Saftey \times Production\ Lost \times Maintenance\ Cost) \tag{3.5}$$

Subject to,

$$\begin{array}{ll} PoF = \mathbf{1} & for\ a\ failure\ event \\ 0 \leq PoF < 1 & Potential\ failure\ or\ a\ fault \end{array} \tag{3.6}$$

Risk index is a better measure as it is quantitative rather qualitative. Risk Index, as estimated from Equation 3.4, helps to establish the level of failure analysis required. It is a numerical value ranging from a minimum value to a maximum value. The higher is the consequence and probability of failure, the higher would be the risk index. As an example, for a 3 X× 3 matrix with three consequence categories, the max value is 9. Risk index will range from 0 to 9, hence guidelines can be developed to categorize the level of assessment using RI.

3.1.3 Analysis Phase

In this phase, all the activities related to failure investigation are performed. Most of the companies have systems or preferred methods in place to conduct formal and informal investigations. However, not all follow a structured approach for the complete process. Simple 5-Why approach for simple failures and other complex techniques for formal investigations can be used. The proposed framework can be effectively used for both formal and informal investigations. There are three key steps in this phase which focus on the identification of the root cause(s) and the corrective actions.

3.1.3.1 Develop Historical Timeline

In this step, historical time sequence of the events prior to failure is established which includes the events and other critical information with data and time as shown in Figure 3.7. Failure timeline provides extremely useful information and suggests the changes made during the life of the equipment, from design to operation. This information is extremely important and the timeline must be factual, precise, and quantified to ensure its best use.

3.1.3.2 Perform Root Cause Analysis

Root cause analysis is the heart of the proposed framework. After establishing a failure or fault incident, possible failure modes based on the information are developed and also the actions or causes that contribute to the failure mode are also developed. At this stage, all the causes to failure modes are hypothetical before evidence is obtained to support the real cause of a specific failure mode. All the technical possible failure modes are generally evaluated to ensure thorough investigation. Once all hypotheses are developed, they are rejected or accepted with the sound engineering knowledge, and facts based on laboratory test results. If the possible cause cannot be rejected, it should have a recommendation for it. In general, there are more than one causes of a failure so all the causes must be supported by well documented evidences and facts. There are some chronic challenges in this step like stopping too early with multiple root causes, or mistaking a symptom for a root cause, is very common. In this step, we identify the root cause(s) and use all the test results, material analysis and information from previous steps to make decisions.

3.1.3.3 Identify Root Cause(s)

Once the root cause analysis step is complete, the next step is the classification of the direct and contributing causes. Physical, human and latent causes are classified. There may be more than one cause of a failure, so it must be ensured that the possible failures have been explored. Root cause must be supported by factual data and evidences. This is also a critical step which may lead to repeat failures if the real root cause(s) are not identified.

3.1.4 Implement and Track Phase

This phase is extremely important for the success of the investigation process, as the real value of the complete assessment process lies in the implementation of the recommendations. It is very common in industry to implement the main recommendation and move on with the operations and ignore or overlook the remaining recommendations.

The poor implementation and tracking of recommendations is one of the basic causes of the repeat failures. In this phase, it is suggested that the recommendations are classified based on a prioritization matrix. The implementation priority is decided by the fact that how much a recommendation is contributing in avoidance of the failure. The stronger the correlation, more chances are that it will get a high priority.

3.1.4.1 Develop Corrective Actions

Proper and effective corrective actions and their implementation is a barrier to repeat failures or a failure in case of minor fault. Once the root cause(s) are identified, proper, effective and smart recommendations must be developed. The corrective action must be specific and open ended recommendations must be avoided. The corrective action must be technically feasible and should not be an over kill, thereby making the system over-designed. There are disadvantages of the poor corrective actions which may not be addressing a root cause and may shift failure to other weaker components or parts of the system.

3.1.4.2 Prioritize and Implement

There are certain ways to classify recommendations. Critical recommendations are the ones that have a greater impact on continuous operation and should be implemented first. Impact and difficulty matrix can be used to classify low hanging fruits. An example of the modified priority matrix is shown in Figure 3.5 [6].

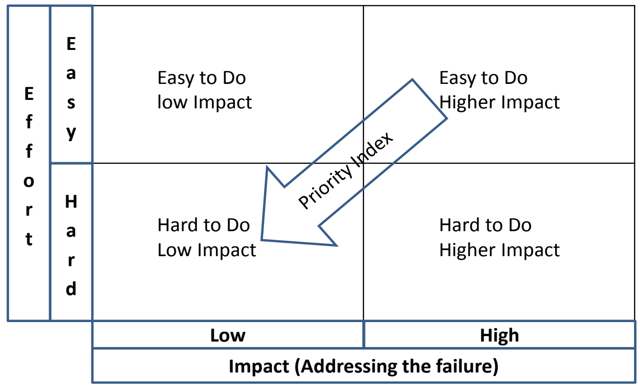

Figure 3.5: Prioritization matrix for corrective actions

Priority Index (PI) can be calculated as,

$$Priority\ Index\ (PI) = Impact \times Effort \tag{3.7}$$

Subject to,

$$\begin{array}{ll} Impact & Low\ (1-5)\ or\ High\ (6-10) \\ Effort & Hard\ (1-5)\ and\ Easy\ (6-10) \end{array} \tag{3.8}$$

Priority Index (PI) is mainly a quantitative measure which suggests which corrective action or recommendation should be implemented first. The higher the priority index, the more beneficial is the corrective action for the company's flawless operations. A company-wide recommendation management system is a solution to this issue to ensure proper implementation of all the recommendations.

3.1.4.3 Track and Monitor

The last step of the proposed methodology is about tracking the implementation of all the recommendations and to monitor the effectiveness of the corrective actions. Some recommendations and changes need a long time to implement as people retire, change jobs, go on vacation, etc. The probability of losing good recommendations is very high. A formal management system is highly recommended. Once all the recommendations are completed, the investigation should be closed in the system, which tells the team that all the corrective actions have been implemented. The monitoring feedback mostly uses performance indicators to evaluate the quality of the investigation and corrective actions. System availability is a parameter to track and evaluate the quality of the investigation and the effectiveness of the recommendations.

3.4 Application of Proposed Approach using Case Studies

Equipment fails and failure assessment is performed to identify the root cause(s) and corrective actions to avoid repeat failures. Failure assessment is also conducted on faults which may lead to a failure like "near-miss" in safety terminology. So, it is critical to conduct the fault assessment. In processing facilities, consequences of a failure are humongous, both financially and in terms of safety. Section 3.4 discusses the two real case studies to demonstrate the proposed methodology and their impact on system availability.

3.4.1 Case Study: Bearing Failure

In rotating machines like pumps and compressors, bearing is an important component and is often proactively monitored for proper functionality through predictive tools. In this case [22], there are two motors driving solvent pumps to supply solvent to a column, as shown in the schematic in Figure 3.6. These pumps have n+1 redundancy and are critical to the continuous operation of the plant. In this event, the plant experienced unwanted interruption in production, when both pumping systems failed due to a common failure mode.

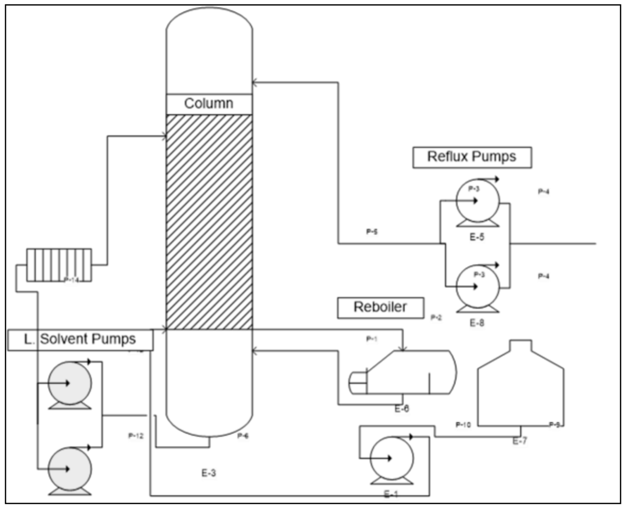

Figure 3.6: Pumping system

The risk-based failure assessment methodology comprising of the four phases, as described in Section 3.3, was applied and is briefly discussed in the following Section.

3.4.1.1 Plan Phase

Failure assessment process was started with the reporting of the incident in maintenance management system and failure assessment was requested. Along with failure report in maintenance management system, the failure mode and the related preliminary data was recorded. The investigation was assigned to a trained engineer to lead the assessment. Following step 2 of the plan phase, the site was preserved, and the initial findings were collected from the field. Along with this activity, preliminary information via interviews, plant online information system was used to collect the online data like process conditions, equipment datasheet, maintenance history, cross-Sectional drawings, before setting up an investigation team.

3.4.1.2 Assessments Phase:

Based on the collected information, subject matter experts were invited to effectively evaluate the failure with the available information. With all the information and the right people, failure consequence assessment was performed using a consequence assessment criterion as per Figure 3.4, to identify the scope and level of this investigation. Risk index suggested that this incident required a formal failure investigation as it involved a major financial consequence. After the assessment phase, it was concluded a formal failure investigation be performed.

3.4.1.3 Analysis Phase

The first step in the analysis process was to develop an incident event timeline as shown in Figure 3.7.

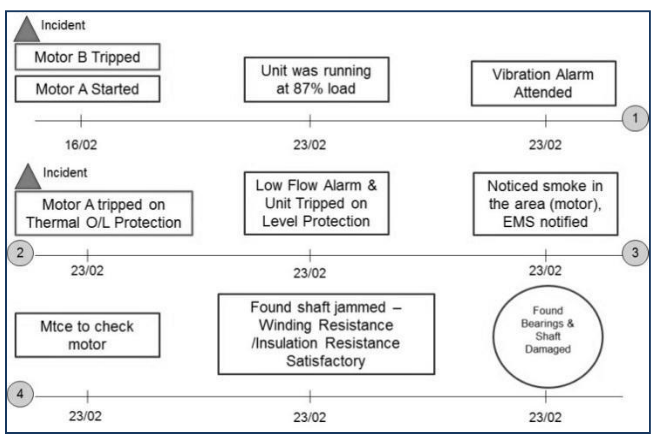

Figure 3.7: Failure event timeline

In the event timeline, all the key critical events were captured to understand the operations and maintenance of the equipment. The transient condition experienced by the equipment was also captured during the timeline to assess the impact of transients. Once the timeline was developed, the identified failure was chosen and identification of possible failure modes was started.

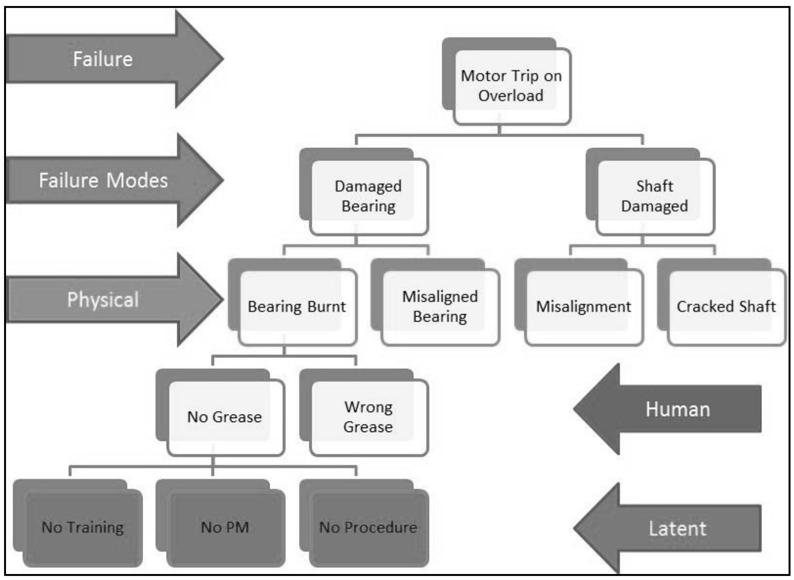

Figure 3.8: Failure cause relationship tree

After selecting the possible failure modes, possible triggers or actions which could cause the failure mode were developed with the help of expert knowledge and the available information. After developing these actions, called hypotheses, they were assigned to team members to work on to accept or reject them, based on the data or engineering experience supported by theory or the inspection of failed parts or using the material analysis reports and the results as shown in Figure 3.8 and 3.9. In this case, there was strong evidence of bearing failure supported by the inspection of failed parts and the vibration data as provided in Figure 3.9 and 3.10. The bearing failure frequency matched with the bearing ball pass frequency, which is solid evidence that the failure initiated at the bearing balls. The root causes may be physical, human or latent but accepted propositions should be used to identify the root causes.

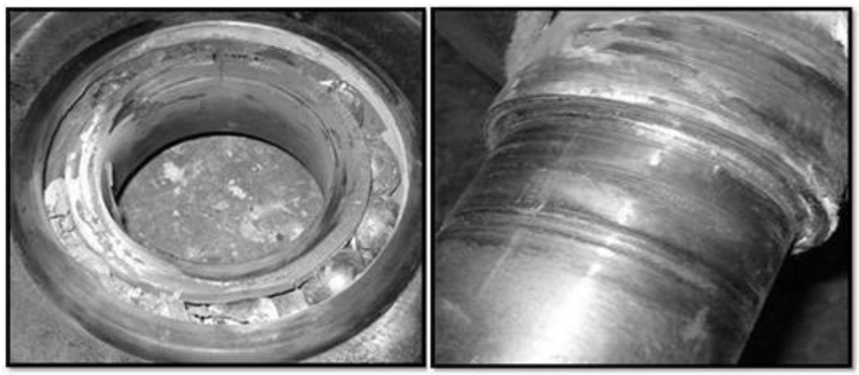

Figure 3.9: Evidence – failed part condition

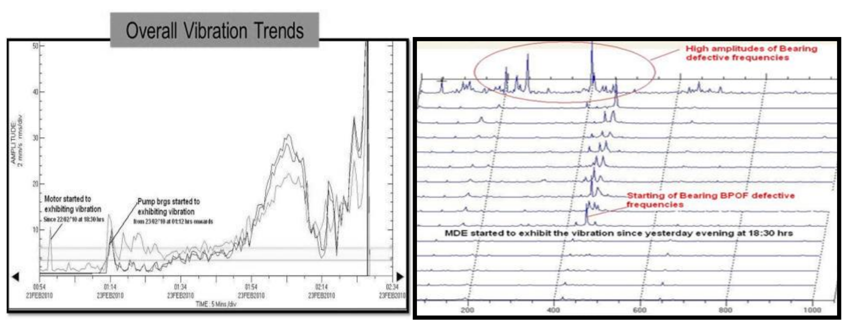

Figure 3.10: Vibration Trend – overall vibration and bearing frequency

3.4.1.4 Implement and Track Phase:

After identifying the root causes, effective recommendations were developed and prioritized using a prioritizing matrix. All the recommendations were not critical; some were critical for the operation of the repaired equipment and some were good to improve the design. Prioritization was performed using the matrix as given in Figure 3.5 to ensure the critical recommendations were implemented first and the remaining recommendations followed thereafter. During the last phase, the focus was to ensure the recommendations were implemented and that they have addressed the real root causes by monitoring the equipment performance.

3.4.1.5 Availability Estimation:

Failure assessment was performed using a structured approach which greatly helps in improving the availability of the system. As shown in Figure 3.6, the failure of both the pumps greatly affected the availability of the system. It caused process interruption which affected both safety as in terms of flaring and production loss. Availability was estimated by using Equation 3.2. Equipment data was analyzed and converted into system level which is summarized in Table 3.1.

Table 3.1: Failure and Repair Data of Pumping System

System (Equipment)	System Mean Time Between Failure (Months)	Mean Time to Repair (Months)
Lean Pumping System – at failure	3.49	0.05
Lean Pumping System – 6 years	34.48	0.06

Availability is estimated using the above mean time between failures and mean time to repair. Significant system availability improvement is experienced between the failure and 6 years period. The structured failure assessment also helps in understanding the nature of the failure, to order spare parts, lacking in training and other influential factors, hence, improving maintainability. System standby redundancy model is used to estimate the system MTBF and availability [23]. Based on the physical plant configuration, appropriate models can be used to estimate mean time between failures and system availability.

MTBF of an active redundant system is given by,

$$MTBF = \int_{0}^{\infty} R(t)dt = \frac{2}{\lambda} \tag{3.9}$$

Availability of an active redundant system with failure rate λ and repair rate μ is given by,

$$Availability = \frac{\sum_{i=N-1}^{N} \mu^i / i!\,\lambda_i}{\sum_{i=0}^{N} \mu^i / i!\,\lambda_i} \tag{3.10}$$

Where, N = Number of Equipment, λ = Failure Rate, i= Number of Active Equipment and μ = Repair Rate

For two equipment redundant system, Equation 3.10 can be simplified as,

$$System\ Availability = \frac{\mu^2 + 2\mu\lambda}{\mu^2 + 2\mu\lambda + 2\lambda^2} \tag{3.11}$$

Summary of availability estimation comparison is shown in Table 3.2.

Table 3.2: Results – Availability Improvement

Pumping System	Availability
Lean Pumping System - at failure	29.1%
Lean Pumping System - 6 years	94.3%
Improvement (Change)	65.2%

3.4.1.6 Results

True identification of the failure causes along with their corrective action implementation greatly expands the availability and reliability of the equipment. Availability is improved by 65.2% points whereas significant improvement in MTBF is also realized using the proposed risk-based approach. The structured process helps developing the confidence of the team by using a consistent and structured proposed methodology. This structured failure assessment approach also helps in identifying the other underlying issues during investigation i.e., system maintainability, critical parts required to improve maintainability and other latent issues of training and procedures.

3.4.2 Case Study: Drive Coupling Failure

Coupling is an essential component of rotating machinery. The main function of a coupling is to transmit torque to drive equipment from a driver and compensate for slight misalignments. Misalignment can be due to installation error or limitations and operating conditions. The failure of a coupling means failure of the system. The proposed approach was used to investigate the failure of the coupling. The methodology suggested in Figure 3.3 was used for identification of root cause(s), manage recommendations and estimate the availability enhancement. The system configuration is given in Figure 3.11. The system consisted of 5 centrifugal pumps where 4 out of the 5 were required to operate the system at 100% load.

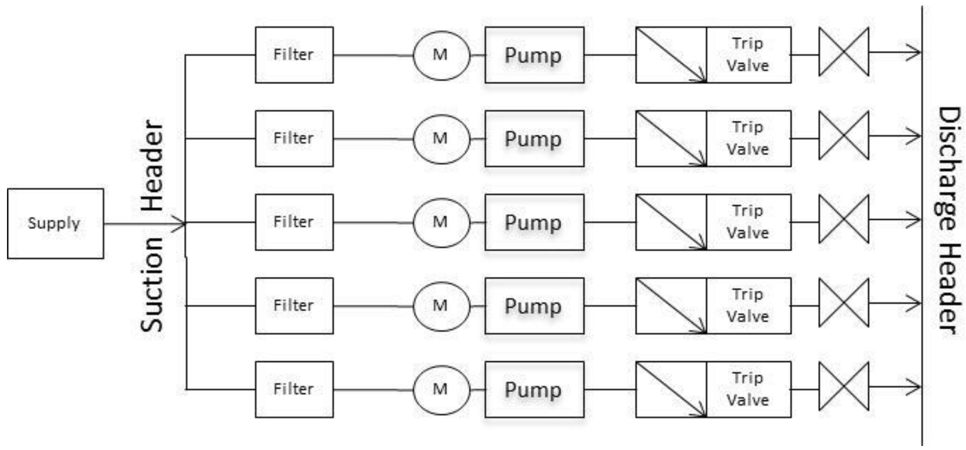

Figure 3.11: Simple supply system configuration

3.4.2.1 Plan Phase

As discussed earlier, the investigation process started with the reporting of incident in maintenance management system along with the request to conduct failure assessment. The failure report in maintenance management system, the failure mode and the related preliminary data were recorded. The site was preserved, initial findings via plant personnel interviews and plant information system were collected prior to initiating the investigation.

3.4.2.2 Assessment Phase

A team was formed to investigate the incident. The team, with all the information and subject matter experts, performed failure consequence assessment using a consequence assessment criterion as given in Figure 3.4 to identify the scope and level of the investigation. Risk index suggested that this incident required formal failure investigation as it involved a major financial consequence.

3.4.2.3 Analysis Phase

The process started with development of an event timeline. Event timeline provides very useful information about the historical events. In event timeline, all the key critical events are captured to understand the operations and maintenance of the equipment. The transient conditions like startup, trips and shutdowns experienced by the equipment are also captured during the timeline to assess the impact of transients. This failure incidence happened during the startup of the facility when the equipment usually experiences multiple startups and trips. This information was very useful while performing the investigation and can be obtained from the event timeline. From the developed timeline, identified failure was taken and identification of failure modes started.

Figure 3.12: Coupling and bearing failure

In this failure event, the only focus on component failure analysis could have led to the wrong root cause. The proposed methodology was employed to evaluate all the possible failure modes and possible causes. In this incident, both the failed parts are consequential to improper or wrong operation and design. The failure of the coupling and bearing was caused by the forces exerted by the reaction forces during the trip or shutdowns from the discharge header as shown in Figure 3.13. Usually, during commissioning and startup the system experiences many startups and shutdowns and that is what this system also experienced. Under these events of shutdown and trips, the flow suddenly stopped as the trip valve shuts down quickly and the back pressure from the discharge header exerted a pressure on the pumps which caused them to move against the direction of flow as shown in Figure 3.14. The pumps kept running under misalignment and experienced this failure. This phenomena of pump movement caused misalignment which exceeded the allowed tolerances.

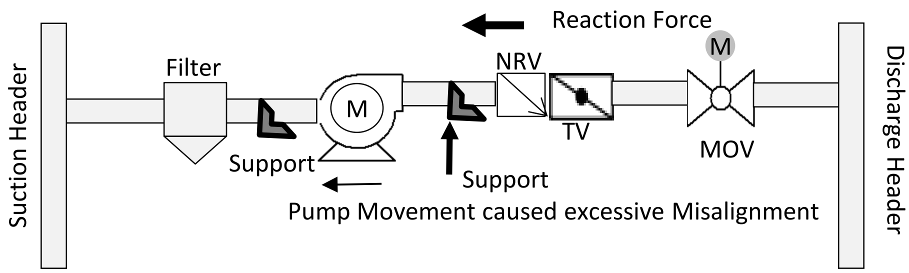

Figure 3.13: Forces on pump caused excessive movement

Couplings are designed to work with small misalignments but in this case, the misalignment exceeded the design limits and continuous operation under excessive misalignment caused the coupling to fail.

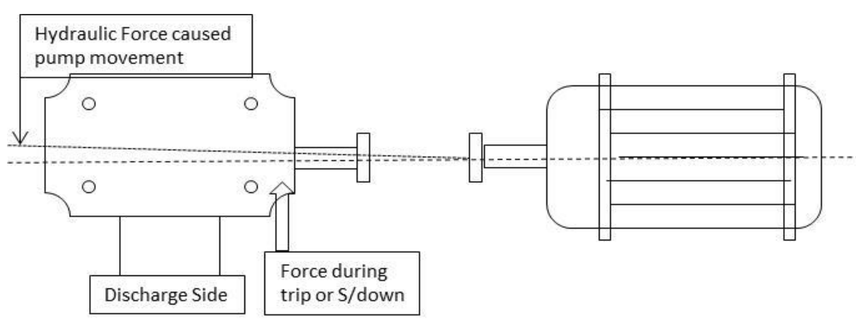

Figure 3.13: Pump misalignment condition

A support system was available to counteract the hydraulic forces in case of trips and shutdown but was found broken. This supported the fact that the reaction forces were higher than the design strength. All the measurements and component analysis was done to ensure the wrong operation and insufficient design were the causes that contributed to this event.

3.4.2.4 Implement and Track Phase

After identifying the root causes, recommendations were developed and prioritized using a prioritizing matrix as shown in Figure 3.5. The prioritization matrix helped in selecting the critical recommendations which were implemented first, before the less important corrective actions. As a corrective action in this case, the operating philosophy was changed, improvement in the strength of the supports along with other recommendations. During the last phase, the attention is to ensure that the recommendations have been implemented and they have addressed the real root cause by monitoring the equipment performance during tracking. In the last, estimated the availability and failure rate to ensure root cause was correctly found and the right corrective action were developed and implemented.

3.4.2.5 Availability Estimation:

A structured approach has proven to be a great tool in enhancing availability of the system. As shown in Figure 3.12, the failure of multiple pumps greatly affected the availability and reliability of the system and caused process interruption and production lost. In this case, availability estimation is performed to evaluate the improvements. System MTBF for N equipment is given in Equation 3.11.

$$System\ MTBF = \frac{2}{(N-1)\lambda} \tag{3.12}$$

For the system shown in Figure 3.11, the Equation 3.11 becomes,

$$System\ MTBF = \frac{1}{2\lambda} \tag{3.13}$$

System failure rates are given in Table 3.3,

Table 3.3: Failure and Repair Data of a Pumping System

System (Equipment)	System Mean Time Between Failures (Months)	Mean Time to Repair (Months)
Pumping System – at failure	4.38	0.5
Pumping System – 6 years	41.66	0.6

Equation 3.11 is used to estimate the availability of this system and the equation as expanded for four out of the five system configurations is given below.

$$System\ Availability = \frac{\mu^5 + 5\mu^4\lambda}{\mu^5 + 5\mu^4\lambda + 20\mu^3\lambda^2 + 60\mu^2\lambda^3 + 120\mu\lambda^4 + 120\lambda^5} \tag{3.14}$$

System availability before and after is given in Table 3.4,

Table 3.4: Results – Availability Estimation

System (Equipment)	Availability
Pumping System - at failure	16%
Pumping System - 6 years	98%
Improvement (Change)	82%

3.4.2.6 Results

The proposed risk-based approach has shown excellent results for identifying root causes(s) and ensuring implementation of corrective actions; leading to improved MTBF and system availability. Table 3.4 shows significant improvement in availability from 16% to 98%. The low availability of the system at the start is due to multiple infant mortality failures. The system did not experience critical failures after the failure assessment using the proposed RBFA approach, which supports the effectiveness of the proposed approach.

3.5 Critical Success Factors – RBFA Methodology

Many lessons have been learned during the development and implementation of this approach. Some of them are extremely crucial for the success of a critical investigation. A listing of the salient features is given below, which will help in addressing the critical points in similar situations.

1. The proposed process must be followed: A proper understanding of the structured process is required.

2. Communication: A proper communication platform should be available to ensure that the cross-functional team has proper and timely information.

3. Team members: The team leader must be properly trained on the methodology and other facilitation techniques. Other team members must be knowledgeable and skilled in the area of the investigation.

4. Tracking and implementation: Experience has shown that most of the repeat failures are the result of a lack of implementation of the recommendations or corrective actions. A suitable and traceable recommendation management system should be developed.

5. Recognition: Team efforts should be appreciated by management to ensure team motivation and development of a proactive reliability culture in the organization.

3.6 Conclusion

The proposed risk-based failure assessment methodology has shown far-reaching improvements in handling equipment fault and failures to enhance safety and availability. Risk-based quantitative analysis to identify the level of root cause analysis and corrective action prioritization is extremely effective and efficient. The proposed method can be equally applied on potential failures and faults to proactively address the potential failure;

greatly reducing the maintenance costs and loss production events. Learning of an assessment can be shared and applied to other similar equipment, which can optimize the maintenance and maintainability. Highly encouraging results have been accomplished from the implementation of the proposed framework. In this work, the presented cases have shown great improvements in system availability; 65.2% in case 1 and 82% in case 2. The proposed approach is user friendly and can be used by following the step by step process. A software solution will greatly enhance the efficiency of the failure assessment process along with the other benefits of data structuring and availability. There are other methods that complement improvements in availability; but the proposed risk-based approach suggests an optimal and effective solution to a general industry problem of repeat failures and faults.

CHAPTER 4

SYSTEM AVAILABILITY ENHANCEMENT USING DECISION TREES [4]

Abstract

System availability is a key performance measure in the process industry. It ensures continuous operation of facilities to meet production targets, personnel safety and environmental sustainability. Process machinery condition assessment, early fault detection and its management are vital elements to assure overall system availability. These elements can be explored and managed effectively by extracting hidden knowledge from machinery vibration information to improve plant availability and safe operations.

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[4] *This Chapter is based on the published work in a peer-reviewed journal. Qadeer Ahmed, Fatai A. Anifowose, Faisal Khan (2015), "System Availability Enhancement using Computational Intelligence based Decision Tree Predictive Model," Accepted in Journal of Risk and Reliability Engineering. To minimize the duplication, all the references are listed in the reference list. The contribution of the authors is presented in Section titled, "Co-authorship Statement".*

This Chapter describes a Decision Tree (DT) based computational intelligence model using machinery vibration data to detect machinery faults, their severity, and suggests appropriate actions to avoid unscheduled failures. Vibration data for this work were collected using a machinery simulator and real-world machine to show the applicability of the proposed model. Later, the data was analyzed to detect faults using DT based model that was developed in MATLAB. Fault detection classification accuracies of 98% during training and 93% during testing showed excellent performance of the proposed model. The suggested model also revealed that the proposed formulation has capability of detecting faults correctly in the range of 98% to 99%. The results highlight that the suggested predictive decision tree based model is effective in evaluating the condition of process machinery and predicting unscheduled equipment breakdowns with better accuracy and with reduced human effort.

4.1 Introduction

Early fault detection and management (FDM) are two main aspects of successful and continuous plant operations at low cost. Computational intelligence and technological advancements have provided us a platform to develop intelligent systems where machinery vibration data and process information can be used for assessing equipment health. Equipment vibration and process information have proven to be very effective in performing fault diagnostics and prognostics to improve the overall availability, reliability and maintainability of complex operating systems. Proper analysis of vibration signals is an important tool that enables engineers to timely detect and identify faults to avoid system failures. Although faults and failures are synonymously used in industry but they represent different equipment conditions. In simple terms, a fault is a state where the equipment is functional but with degraded performance or does not function properly when required [1]. A failure is described as a condition where the equipment fails to perform its defined function and is in a state of a complete breakdown [2]. To avoid failures and keep repair costs in control, faults should be detected and managed efficiently during their infancy stage. Proper maintenance action helps in managing faults to avoid failures, which usually costs three to four times higher than a planned repair cost [3]. Presently, vibration data are usually collected during routine maintenance and analyzed by operators to assess the condition of equipment. This assessment is very much dependent upon the skill level of the operator and any wrong interpretation can have negative consequences. Early and correct detection of faults and its management help improving availability by addressing both dependencies of availability, i.e. reliability and maintainability as presented in Equation 4.1.

$$Availability = \frac{Reliability\ (MTBF)}{Reliability\ (MTBF) + Maintainability\ (MTTR)} \tag{4.1}$$

where, MTBF = Mean time between failures and MTTR = Mean time to repair.

Equipment condition, maintenance cost, operating time and overall risk are interrelated as shown in Figure 4.1. In this figure, the x-axis represents the operating time and the y-axis represents the equipment condition and influence of cost. The C_1 range represents the equipment with minor signs of degradation; the C_2 range shows the signs of some damage; and C_3 is the condition where the condition is worst and major action is required. F is a point where the equipment failed to perform its function and is classified as a point of failure or potential failure. Overall risk of a failure includes failure cost, environmental impact along with personnel safety and production loses. If a fault is detected in zone C_1, the cost and risk would be significantly less compared to the fault that is identified in zone C_3. Early fault detection can be effectively addressed by a normal maintenance action like greasing and tightening of bolts. A fault in the advanced stage would require component replacement and higher repair cost. Due to these benefits, cost avoidance and improvement in plant availability, equipment condition monitoring is gaining significant importance. The outcome of equipment condition based on past history is classified as diagnostics while the prediction of remaining equipment life is generally termed as prognostics, as presented in Figure 4.1. This work mainly focuses toward the fault diagnosis and its management rather than the prediction of remaining useful life.

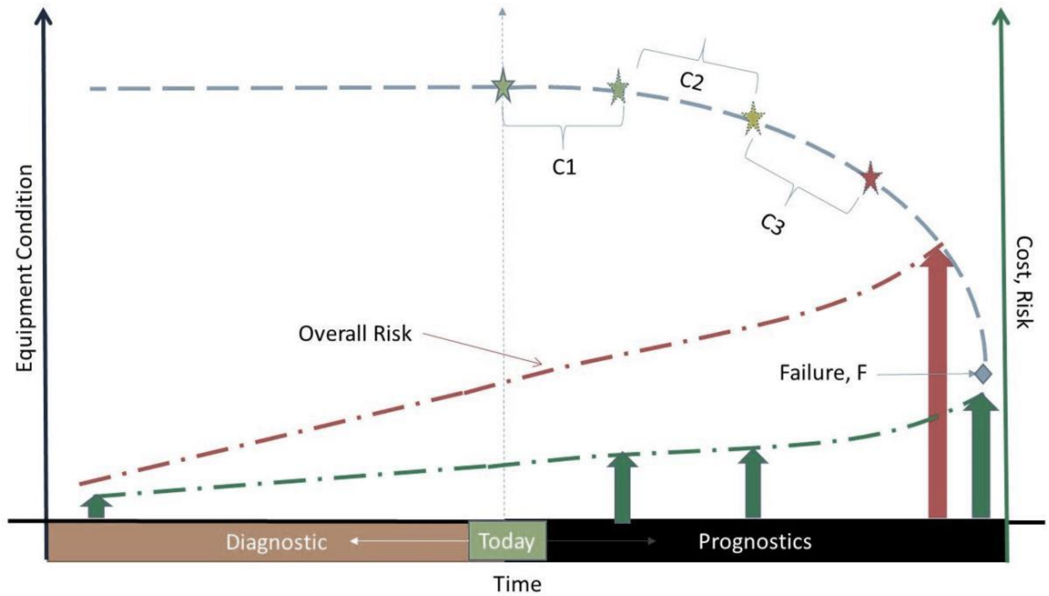

Figure 4.1: Diagnostic-prognostic concept with equipment condition, risk and cost

Machines are complex systems and usually exhibit many faults, however, this research focuses on two faults and they are: unbalance and misalignment. Unbalance is defined as “a condition when the center-of-gravity of the rotor is out of alignment with its axis-of-rotation” [4]. Misalignment is defined as “a condition when relative center lines of shaft of two machines are not in line with each other” [5]. These two faults are top contributors to machine diagnostic processes and among 90% of the reported faults in machinery failures [6]. Vibration data in fault detection is extremely helpful as a fault in a machine can be represented by frequency components and their severity by signal amplitude. Figure 4.2 shows the general spectrum of the unbalance and misalignment where good understanding of spectrum, component frequencies and signal amplitude limits greatly helps in fault detection.

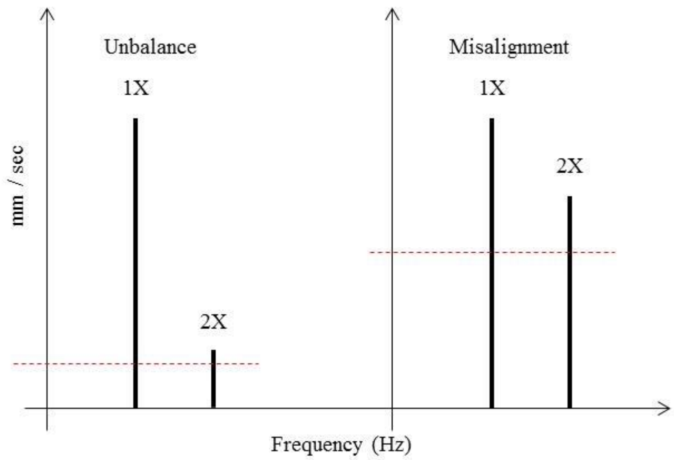

Figure 4.2: Spectrum snapshot of misalignment and unbalance

Presently, fault diagnosis is carried out using different condition monitoring techniques, i.e. oil condition monitoring, vibration and other process parameters monitoring. These methods are prone to human errors, excessive man-hours, and are sometimes inaccurate due to the misunderstanding of the correlation of these parameters for a single output. To ensure effective prediction and generalization, all known possible machine conditions and fault scenarios should have representation in the training data. To address this limitation, suggested model formulation is dynamic and easily updated to allow the addition of new possible scenarios without having to re-model from the scratch. Second, it is based on the machine learning paradigm rather than the conventional statistical interpolations, due to these reasons, its improved and robust performance is guaranteed. The proposed computational intelligence based holistic fault diagnostic and management scheme methodology utilizes machinery and simulator data to predict faults, their severity using decision tree (DT) algorithms

Computational intelligence through data mining offers promising methods to extract hidden information patterns from these datasets, which are extremely difficult to discover with simple statistical analysis. These hidden patterns can be explored and used to predict some future trends with good quality data. Data mining can be done using different techniques. Some of the most popular methods are: classification, clustering, deviation detection and estimation etc. We are focused on classification as we predict using a pre-labeled classified condition; i.e., machinery unbalance and misalignment. Classification is a robust method for predicting the illustration class from pre-labeled instances. Classification is an important task in data mining where a classifier is built based on some attributes to describe the objects or one attribute to describe the group of the objects. Later, the classifier is used to predict the group attributes of other cases [7].

The remainder of the Chapter is organized as follows: Section 4.2 discusses the present state of literature and the work performed in the field of fault diagnostics using smart algorithms. Section 4.3 provides the formulation of the proposed fault detection model and fault management strategy. Section 4.4 describes the detailed research methodology including data collection, experimental setup, the criteria used to evaluate the performance of the model and the validation of the model with real operational data. Section 4.5 presents the results with discussion. Conclusions and the contributions are highlighted in Section 4.6.

4.2 Literature Review

Fault diagnostics using condition monitoring has become an area of great interest in industry. The capability of detecting an early fault enables engineers and operators to reduce the probability of damage and loss. Faults, if not addressed properly can have catastrophic consequences in terms of lost production, maintenance costs and safety. Due to these reasons, a number of data mining and optimization techniques have been applied to fault classification, diagnostics and its management [8-14]. We have explored a holistic data-driven model, where the focus is on detection and management of faults. In data driven modeling approach, the available data is generally used to learn hidden patterns and extract knowledge to detect faults. Academic and industry researchers in the field of artificial intelligence, pattern recognition, and data mining have considered DTs as an effective technique. This is one of the reasons for exploring DT for the problem at hand. Many researchers have used artificial intelligence algorithms to detect machinery faults and some of them are discussed in this Section. Support vector machine (SVM) models (c-SVC and nu-SVC) with four kernel functions were used for classification of faults using statistical features extracted from vibration signals under good and faulty conditions of rotational mechanical system [15]. A DT algorithm was used to select the prominent features. These features were given as inputs for training and testing the c-SVC and nu-SVC model of SVM and their fault classification accuracies were compared. We are targeting a simpler model compared to hybrid DT-SVM model but with improved, or at least competitive, detection accuracy. In another work, DT was used for fault detection in bearings using sound signal [16]. Data was collected from the near-field area from good and faulty bearings with classification accuracy in the range of 68.8 - 95.5%. To detect motor faults, DTs were also used in another work [17]. A layered dynamic hybrid fault modeling and extended evolutionary game theory was proposed for reliability, survivability and fault tolerance analysis [18]. Due to the complexity of the model, the authors recommended development and implementation of a software program. The DT model of this work ensures simplicity of implementation with good accuracy. Risk is an important aspect to evaluate the consequences of certain faults or failures in complex systems. The operation of such complex systems involves multiple hazards and consequences in case of breakdown. This makes the area of risk assessment and quantification extremely important and related to fault detection and management, availability and maintenance of the systems. To study the relationship between risk, availability and its consequences in certain scenarios, a risk-based availability analysis model is presented [19].

As discussed above, fault diagnostics and prognostics through monitoring condition data have merits. Some of these fault diagnostics techniques are explored further to express the novelty of this work. A DT-based formulation is developed to identify the causes of the abnormal vibration [20]. This work mainly focused on automating the vibration diagnosis process for rotating machinery, which is applicable to vibration diagnosis expert system rather than detecting faults. Fault diagnosis using DTs is carried out using vibration signals from a gear box [21]. Features were extracted from vibration data and important features were used to develop a classification model using a DT algorithm. This work is more focused on helical gear application and general abnormality detection rather than finding specific faults. In another work, vibration signals from a bearing are used to collect condition data and develop a pattern to establish conditions [22]. The statistical features are extracted from vibration signals and representative features that discriminate the different fault conditions of the bearing are selected using a DT. A rule set is formed from the extracted features and input to a fuzzy classifier based on intuition and domain knowledge. Later, the fuzzy classifier is developed and successfully tested. Fault diagnostics has gained momentum and the latest technologies have been adopted to detect faults. In [23], data mining is used for fault diagnostic where DT-based principal component analysis is proposed. Principal component analysis is used to extract features and a C4.5 algorithm is used for training. A laboratory simulator was used to simulate faults such as unbalance, shaft cracks, etc. The results show that DT-based principal component analysis is a better method compared to other advance methods such as back-propagation neural networks. In another work, bearing defects in rotating machines is explored by identifying expert rules [24]. Data are collected from vibration signals measured in an experimental setup to determine statistical parameters. The DT is then constructed by applying a C4.5 algorithm on the dataset, and so expert rules are established to detect faults. DTs have been used in a number of previous studies but ours is more rigorous and exploratory as we considered and implemented a number of innovative approaches to the machine-learning based modeling paradigm. These mainly include:

i. Using a stratified sampling methodology to ensures that each data sample has an equal chance of being selected for training or validation which allows a good mix of representative data samples.

ii. In addition to condition monitoring and prediction, our methodology includes the prediction of the levels of the severity of the machine conditions and how to manage the fault condition.

iii. The data sets used were obtained from a rigorous experimental procedures and real machine operating scenarios therefore, more comprehensive and better representation of real machine fault and operating conditions.

The presented work consists of a fault and its severity assessment. Later, the fault management strategy is implemented that addresses the handling of detected fault condition, efficiently, which is indeed a requirement while working in real plant situations.

4.3 Proposed Fault Detection and Management Framework

A health assessment for equipment mainly depends on an effective fault diagnostics and management process. In this work, identification of a fault, its location and severity is mainly a diagnostic activity and estimation of a condition based on the severity of the fault, along with its impact on the operating system, is part of the fault management task. The proposed framework has three main steps: fault detection, fault severity, and management of faults through proper maintenance action. Maintenance actions depend mostly on the severity of the fault, which is established by comparing the fault severity with internationally developed machinery vibration limits. Most failures of rotating equipment appear in a vibration spectrum by some frequencies, and the severity depends on the level of amplitude. Many common machinery faults have a strong relationship with running speed and two important speed factors are unbalance and misalignment, which have been focused in this Chapter. We classify fault severity risk into three categories: low (acceptable), medium (caution) and high (dangerous). The low fault level suggests a machine that can be used continuously with monitoring; medium or caution is a level where it is required to perform some extra monitoring to track the condition of the equipment. The last level is for a high or dangerous condition where the machine must be stopped promptly to avoid a catastrophic failure and a proper investigation shall be performed prior to another startup. The effective usage of the proposed model, as shown in Figure 4.3, will help to avoid catastrophic failures, and therefore improving the availability of the systems in a plant. The proposed framework mainly has three distinct steps, which are discussed in the following Sections.

4.3.1 Fault Detection

In this step, data are acquired along with feature selection. The feature or variable must be carefully selected during model development as the accuracy of classification is greatly dependent upon the right features being considered. Once the features are finalized, we need to categorize the collected data in faults by assigning labels. Data stratification is performed to ensure a good mix of data without any bias. The data are then used in the development of a DT model that provides the results in the form of training, and testing accuracy of the model and its capability of detecting faults.

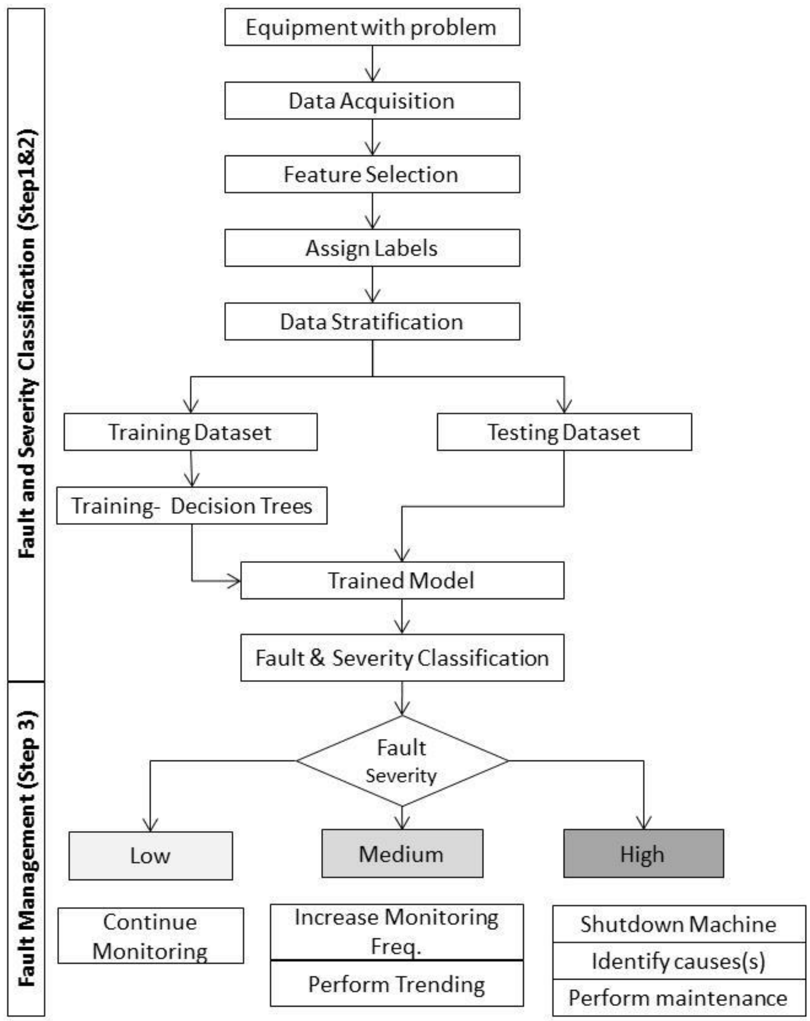

Figure 4.3: Fault detection and management framework

4.3.1.1 Decision Trees in Fault Detection

Decision trees are widely used in many real-life applications, which include control systems, biomedical engineering, object recognition, power systems and many more applications. Decision trees are based on the rules, which depend on human experiences, as well as machinery behavior, which makes it widely used and accepted in fault detection. DTs have other advantages such as simplicity in design and accurate prediction [25]. They are also relatively faster in execution compared to other classification models. In classification models, feature selection is an important process as the accuracy of the outcome is highly dependent on the relativity of the feature with the problem being analyzed. Therefore, to ensure optimal solutions, only the best features must be used. We have tackled the problem uniquely, where a DT algorithm is used to detect machinery faults along with the severity of the fault. The construction of the DT is based on a training set, S, which is a set of different experiments. Each experiment or condition specifies the values for a collection of attributes and for a class. Let the classes be denoted by C_i. There exist experiments with n outcomes that partition the training set K into subsets $K_{i \ldots n}$. Assume that S is a set of cases, $freq\ (C_i, S)$ is the number of cases in S that belong to class C_i, and $|S|$ is the number of cases in set S. If we select a case at random from set S and assume its relationship with classC_i, probability can be computed as,

$$freq\left(C_i, \frac{S}{|S|}\right) \tag{4.2}$$

and the information it provides is,

$$-\, log_2\left\{freq\left(C_i, \frac{S}{|S|}\right)\right\} \tag{4.3}$$

The information required to establish a class of an experiment in S is given in Equation 4.4. The procedure for designing a DT model follows the steps described below:

Step 1: Calculate $Info(S)$ to identify the class in the training set S.

$$Info(S) = -\sum_{i=1}^{K}\left[\left\{freq\left(C_i, \frac{S}{|S|}\right)\right\} log_2 \left\{freq\left(C_i, \frac{S}{|S|}\right)\right\}\right] \tag{4.4}$$

where $|S|$ is the number of cases in the training set; C_i is a class; I $= 1,2,3, \ldots ; K$ is the number of classes; and $freq(C_i, S)$ is the number of cases.

Step 2: Calculate the expected information value, $infoX(S)$ for test X to partition samples in S.

$$InfoX(S) = -\sum_{i=1}^{K}\left[\left(\frac{|S_i|}{|S|}\right) Info(S_i)\right] \tag{4.5}$$

where K is the number of outputs for test, X, S_i is a subset of S corresponding to i^{th} output and is the number of cases of subset S_i.

Step 3: Calculate the information gain,

$$Gain(X) = Info(S) - InfoX(S) \tag{4.6}$$

$$\begin{aligned} Gain(X) = &-\sum_{i=1}^{K}\left[\left\{freq\left(C_i, \frac{S}{|S|}\right)\right\} log_2 \left\{freq\left(C_i, \frac{S}{|S|}\right)\right\}\right] \\ &+ \sum_{i=1}^{K}\left[\left(\frac{|S_i|}{|S|}\right) Info(S_i)\right] \end{aligned} \tag{4.7}$$

Step 4: Calculate the partition information value $Splitinfo(X)$ *acquiring for* S, *partitioned into L subsets,*

$$SplitInfo(X) = -\frac{1}{2}\sum_{i=1}^{L}\left[\frac{|S_i|}{|S|}log_2\frac{|S_i|}{|S|} + \left(1 - \frac{|S_i|}{|S|}\right)log_2(1 - \frac{|S_i|}{|S|})\right] \quad (4.8)$$

Step 5: Classification tree splits nodes based on either impurity or node error [26]. There are three general arguments to split the node and they are:

i. *Gini's Diversity Index:* The Gini index of a node is given by:

$$Gini\ Index = 1 - \sum_{i} p^2(i) \quad (4.9)$$

where the sum is over the classes i at a node, and $p(i)$ is the observed fraction of classes with class i that reaches the node. A node with one class has index 0, otherwise any positive value.

ii. *Deviance Diversity Index*: The deviance of a node is given by:

$$Deviance = -\sum_{i} p(i)logp(i) \quad (4.10)$$

where the sum is over the classes i at a node, and $p(i)$is the observed fraction of classes with class i that reaches the node. A pure node has deviance 0, otherwise it is positive.

iii. *Twoing Index*: It is not a purity measure but a different way to split a node. The Twoing function is given by:

$$Twoing = P(L)P(R)\left[\sum_{i} L(i) - R(i)\right]^2 \tag{4.11}$$

where $P(L) and\, P(R)$ are the fraction of observation that split to the left and right, respectively. In this case, if the expression is large, each node is purer; but if the expression is small each child node will be similar to each other.

Step 6: Calculate the gain ratio,

$$Gain\ Ratio(X) = Gain(X) - \ SplitInfo(X) \tag{4.12}$$

The overall gain ratio is given by:

$$\begin{aligned} &GainRatio(X) \\ &\quad = -\sum_{i=1}^{K}\left[\left\{freq\left(C_i, \frac{S}{|S|}\right)\right\} log_2 \left\{freq\left(C_i, \frac{S}{|S|}\right)\right\}\right] \\ &\quad + \sum_{i=1}^{K}\left[\left(\frac{|S_i|}{|S|}\right) Info(S_i)\right] \frac{1}{2} \sum_{i=1}^{L}\left[\frac{|S_i|}{|S|} log_2 \frac{|S_i|}{|S|}\right. \\ &\quad \left. + \left(1 - \frac{|S_i|}{|S|}\right) log_2 (1 - \frac{|S_i|}{|S|})\right] \end{aligned} \tag{4.13}$$

The advantage of a gain ratio is that it compensates for weaker points in step 3, which represents the quantity of information provided by a training set. This allows the attribute with the highest gain ratio be selected as the root of the DT.

4.3.2 Fault Severity

All the faults in a system have different importance and that was the reason we have chosen to collect the data with a known severity condition, which was used in training and testing. In other words, we have implanted the severity in the fault data during the experiment design. Table 4.2 represents all the tests with different faults and their severity conditions.

4.3.3 Fault Management Strategy

The last part of the proposed approach is fault management, which can only be performed once the fault is detected and its severity is established. The action is mainly dependent on the severity of the fault. If the fault is in the low risk category, continuous monitoring can help to ensure that any further development of the fault is quickly identified. Such faults may actually not be a real fault but the machine's inherent response at that operating level. Later, if the trend increases along with the amplitude of the vibration, it has to be investigated properly using both frequency and time domains to understand the fault. Faults can be investigated using spectrum as certain frequencies in machines represent certain components in machines. The bearing frequencies, gear frequencies, unbalance conditions, and misalignment conditions can be detected using spectrums. Lastly, if a machine experiences very high vibration levels and reaches the reference limits of vibration monitoring standards or other experienced based levels, it must be stopped properly and a detailed root cause failure investigation must be performed to understand the underlying reason of the faults. There are many reference standards available based on the machinery categories [27]. Some of them are ISO/7919, ISO/10816 and ISO 7919-1. These standards also recommend which data are required, and how to collect and analyze the data to extract useful information. As an example, the reference suggests the safe and dangerous operating levels that should be followed when comparing the machine data. Table 4.1 shows the fault management matrix, which contains information about the severity of machine conditions after comparison with the allowed limits of reference vibration for specific equipment. This is only to show that the direction as faults should be managed by taking timely and proper actions rather than waiting for the failure. The corrective action may be different based on the severity of the service of the equipment and may suggest the shutdown even if the equipment is in the medium severity level.

Table 4.1: Fault Management Matrix

Fault Condition	**Fault Severity Levels**		
	Low	Medium	High
Unbalance	1. Continue to operate 2. Collect data 3. Continue monitoring	1. Continue to operate 2. Collect data and trend 3. Increase monitoring frequency 4. Plan to switch over in case of redundant equipment	1. Equipment Shutdown 2. Collect historical data and analyze 3. Obtain spectrum, waveform and analyze 4. Switch over in case of redundant equipment 5. Identify vibration cause prior to startup
Misalignment	1. Continue to operate 2. Collect data 3. Continue monitoring	1. Continue to operate 2. Collect data and trend 3. Increase monitoring frequency	1. Equipment Shutdown 2. Collect historical data and analyze

		4. Plan to switch over in case of redundant equipment	3. May require to open the casing 3. Obtain spectrum, waveform and analyze 4. Switch over in case of redundant equipment 5. Identify vibration cause prior to startup

4.4 Experimental Setup and Data Collection

In this Section, application of the proposed framework is demonstrated. This Section is broken down into two main sub-Sections; i.e., experimental setup and data collection.

4.4.1 Experimental setup

The experimental setup comprised the fault simulator with sensor, data acquisition and experiment as shown in Figure 4.4. A laboratory rotor kit as a rotating machinery simulator was used to closely simulate the actual rotating machine behavior [28]. The rotor kit is capable of simulating real machine faults, which makes it useful for laboratory studies to understand the effect of machine faults and failure modes. The rotor kit consists of a mechanical base comprising the motor, coupling, rotor shaft, two balance wheels, two journal bearings and bearing blocks, six proximity probes, three probe mounts, a rub screw, and three safety covers as show in in Figure 4.4 [28].

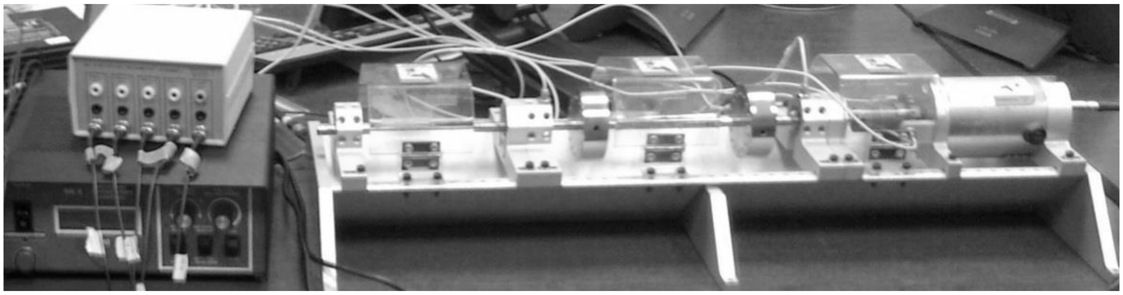

Figure 4.4: Experimental setup in a laboratory

To ensure that all the possible fault scenarios data are collected, an experiment test table was developed as shown in Table 4.2. This table contains all the test requirements, which are capable of providing all the information needed for the validation of the proposed model. Equipment was setup to collect all four vibrations from two bearings, phase angle information and the speed of the machine. From experience and discussion, these are the main features that can help to predict faults and are required for the DT model. The format of the data collection is given in Table 4.3. The overall strategy to develop and validate the proposed scheme is based on three main tasks. The first task is to collect data using certain fault conditions in the laboratory environment. Second task requires to build the DT model in MATLAB to train and test the model using laboratory data. The last task is to collect the data from real plant fault scenarios, validate the applicability of model, and to suggest the actions needed to address the fault condition. The models were implemented in three phases: using the noisy and unfiltered vibration data; using cleaned and filtered data; and using real-life plant data. In the first phase, we estimated the accuracy of the training and testing classification using all the data. In the second phase, the collected data were cleaned by taking out the possible noise areas, i.e. startup data. At the end, we used real machine data to validate the applicability of model in detecting faults in real plant conditions.

Table 4.2: Experimental Setup for the Laboratory Test

	Unbalance	***Misalignment***	***Labels***
Test 1	0	0	0
Test 2	2.2 grams	0	1
Test 3	4.4 grams	0	2
Test 4	0	Minimum	3
Test 5	0	Maximum	4
Test 6	4.4 grams	Maximum	5

Table 4.3: Data Collection Strategy for the Test

Test 1-6	Speed	*DE-X	*DE-Y	*NDE-X	*NDE-Y	Phase(1X)	Overall Amplitude (1X)
Units	rpm	Microns	microns	microns	microns	Degrees	microns

* DE is Drive End and NDE is Non Drive End

4.4.2 Vibration Data Collection

Vibration data collected as Test 1 represents the baseline, which is the "no fault" or a baseline condition. Tests 2-6 represent different fault conditions with different magnitudes. The conditions of the tests were set on the test rig and the data were collected with a certain frequency to ensure the transient or spikes in the data are not missed. Two levels of unbalance data were collected, which were 2.2 grams and 4.4 grams. Two levels of combined misalignment were introduced and classified as minimum and maximum, as it was really difficult to numerically measure and differentiate the angular and vertical misalignments on the machinery simulator kit. Experiments were designed to ensure that all the required data in terms of faults and features are captured for the study. Tests for unbalance and misalignment were conducted independently, and then a worst case scenario of the combined fault tests was run to capture common machine operating conditions. The test plan shown in Table 4.2 ensured that all the critical conditions were considered and tested. It would be noted that Test 6 was designed to run the combined effect of faults with the highest severity. Labels were assigned to the different machine conditions with "0" representing "normal condition" and 5 representing the “worst condition”.

The rotor kit was set up to ensure that it is perfectly balanced with no misalignment. Data were collected to startup and shutdown the simulator for all the fault conditions and a baseline test with no faults. Features that were selected in data acquisition included speed, overall amplitude, 1X amplitude and 1X phase. These features were selected based on engineering understanding and experience with the machines. The target variable was the operational condition of the machine. The data initially consisted of 8,491 samples representing different degrees of these faults. Frequency components of unbalance conditions can be observed in waterfall plots as shown in Figure 4.5. In base condition, there is no significant component of 1X of speed but with the introduction of unbalance, 1X of speed component becomes dominant. There are some other orders can be observed in waterfall plot at different speeds but they are not dominant. A bode plot of an unbalance condition of 2.2 grams is shown in Figure 4.6 to understand the effect of unbalance on amplitude. The change in the magnitudes can be observed as conditions change from no fault to higher level of fault. The changes can also be observed among all four due to the different faults.

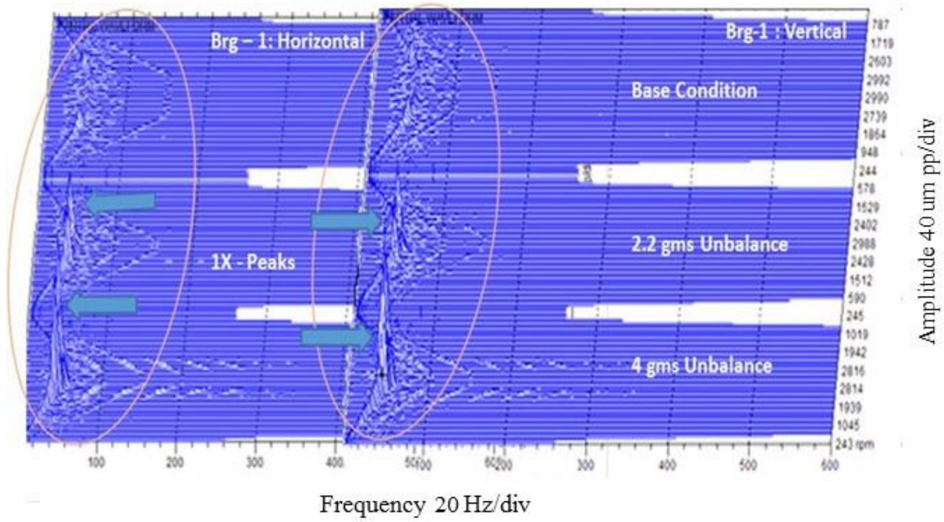

Figure 4.5: Waterfall plot for Unbalance under three different unbalance conditions

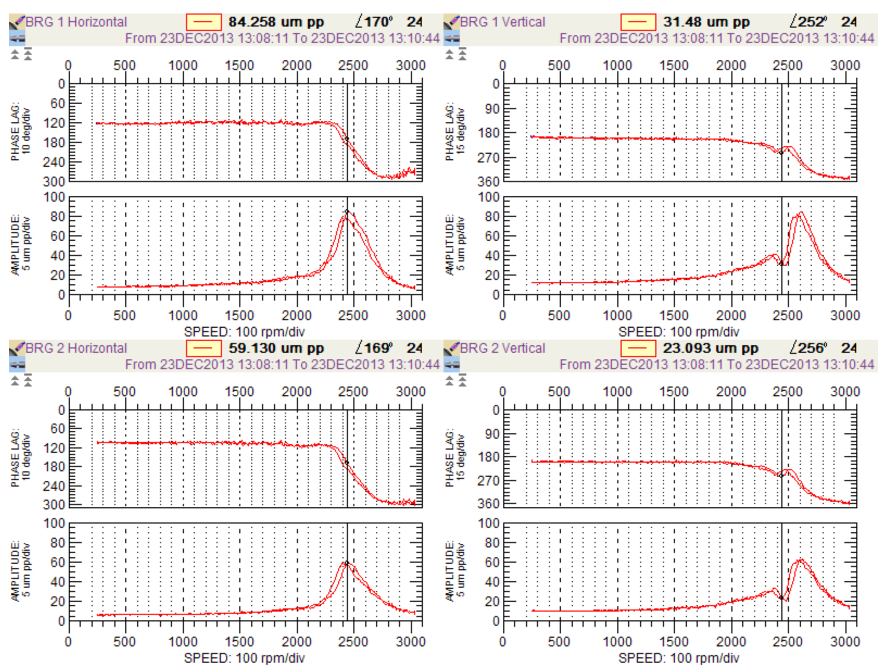

Figure 4.6: Snap Shot of Bode Plots with 2.2 grams of Unbalance

Descriptive statistics of the vibration data, used both from the rotating equipment simulator and real plant, are given in Tables 4.4 and 4.5. The detail of the data used provides statistics for comparative analysis. The common parameters like mean, standard deviation and count, are presented the tables below.

Table 4.4: Equipment Simulator Descriptive Data Statistics

	Speed	Overall Amplitude	Amplitude	Phase
Mean	2183.8	27.0	18.4	155.9
Standard Error	8.1	0.3	0.3	1.0
Standard Deviation	647.4	22.1	22.7	83.1
Sample Variance	419163.9	486.7	513.9	6912.6
Range	2038.0	168.8	169.8	359.0
Count	6460.0	6460.0	6460.0	6460.0

Table 4.5: Real Plant Descriptive Data Statistics

	Speed	Overall Amplitude	Amplitude	Phase
Mean	1537.8	61.9	55.6	183.0
Standard Error	16.0	1.3	1.3	1.5
Standard Deviation	641.9	53.4	53.1	61.9
Sample Variance	412093.1	2851.5	2818.9	3831.0
Range	2324.0	165.4	164.9	270.0
Count	1619.0	1619.0	1619.0	1619.0

4.5 Results and Discussion

Result are presented in two sub-Sections: the first Section will discuss the findings based on the data collected using a laboratory simulator while the second Section will discuss the model validation using real equipment data with a fault condition.

4.5.1 Model Design and Testing using Rotating Equipment Simulator Data

With the noisy and unfiltered vibration data, Tables 4.6-4.8 show the results of the three DT splitting criteria viz. Gini, Towing and Deviance, respectively. Data stratification is part of the model design methodology to eliminate the bias among different label categories. The randomized stratification method was used to ensure that all the fault cases are well represented in the subsets. This was also to ensure fairness in the evaluation of the performance of the models. Using a fixed stratification would have resulted in a set of faults being used in training and others used in testing. This will be unfair to the model performance evaluation. To study the effect of the stratification on the performance of the models, we evaluated three cases with different percentage of stratification viz. 70%, 80% and 90%. With these stratification strategies, 70%, 80% and 90% of the entire dataset was used for training while the remaining data was used for testing. The results of these are summarized in Tables 4.6 through 4.8.

Table 4.6: Fault Classification Accuracy using Gini Index Split

	S – 70%			S – 80%			S – 90%		
Classification	R – 1	R - 2	Avg.	R - 1	R - 2	Avg.	R - 1	R - 2	Avg.
Training (%)	95.6	95.1	95.3	95.7	95.6	95.6	95.7	95.6	95.6
Testing (%)	84.1	85.7	84.9	87.8	86.2	87.0	85.8	86.7	86.2

Table 4.7: Fault Classification Accuracy using Twoing Split

	S – 70%			S – 80%			S – 90%		
Classification	R – 1	R - 2	Avg.	R - 1	R - 2	Avg.	R - 1	R - 2	Avg.
Training (%)	95.1	95.5	95.3	95.7	95.5	95.6	96.3	96.1	96.2
Testing (%)	85.7	86.8	86.2	87.3	85.9	86.6	87.7	87.1	87.4

Table 4.8: Fault Classification Accuracy using Deviance Split

	S – 70%			S – 80%			S – 90%		
Classification	R – 1	R - 2	Avg.	R - 1	R - 2	Avg.	R - 1	R - 2	Avg.
Training (%)	95.5	96.0	95.75	96.3	96.1	96.2	96.0	96.2	96.1
Testing (%)	86.1	86.0	86.0	87.7	87.1	87.4	89.6	88.3	88.9

Classification problems are highly dependent on the features. The use of the most relevant features is capable of greatly improving the classification accuracy. To understand the impact on training and testing classification accuracy, different applicable features were selected and used. Table 4.9 shows the effect of the number of features. The training and testing classification improved from 56.4% to 95.4% and from 30.5% to 85.7%, respectively; which can be observed graphically in Figure 4.7. It was observed that the greater the number of features, the better the models predicted. The gap between training and testing with one feature was 25.9%. This gap significantly reduced with four features to 9.7%.

Table 4.9: Effect of the Number of Features on Average Classification Accuracy

# of Features	Training Classification Accuracy	Testing Classification Accuracy
1	56.4%	30.5%
2	82.4%	58.0%
3	88.7%	71.6%
4	95.4%	85.7%

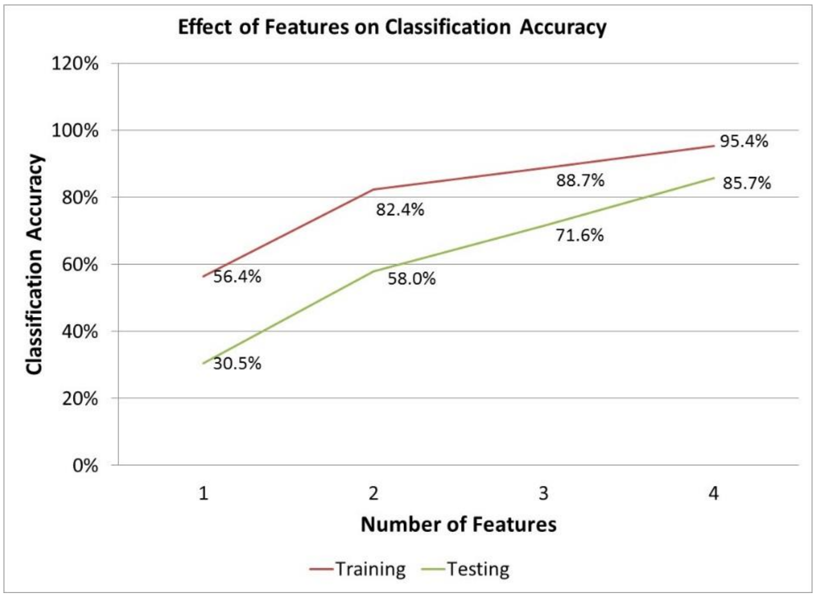

Figure 4.7: Effect of features on classification accuracy

To improve the classification accuracy, the data were reviewed and filtered. Some initial start data were taken off due to the presence of noise and abnormalities. Table 4.10

shows the results after data cleanup and a significant improvement was noticed. The testing classification accuracy was improved by 5-6% and testing accuracy marginally improved by 2%. There was no significant difference noticed among the three split criteria, but the Deviance split performed slightly better than the other two. The stratification effect shows slight improvement in classification as we moved from 70-90%. The combined effect of stratification and splitting criteria can be seen in Figure 4.8. The training and testing graphs correspond to the three training options that are available in the Decision Tree algorithm, Gini, Twoing and Deviance at 70, 80 and 90% stratification respectively. Each of these algorithms has been described in Section 4.3. Gini is the commonly used algorithm, however, we found it necessary to investigate the effect of the other algorithms. Deviance algorithm performed slight better than the other two algorithms in this case. On the average, the slight positive change is not shown only in the 90% stratification but also in the 80%. The reason for improvement, which also confirms our conclusion, is that generalization (testing) improves with increase in the number of training samples, when the proportion of the training stratification increases.

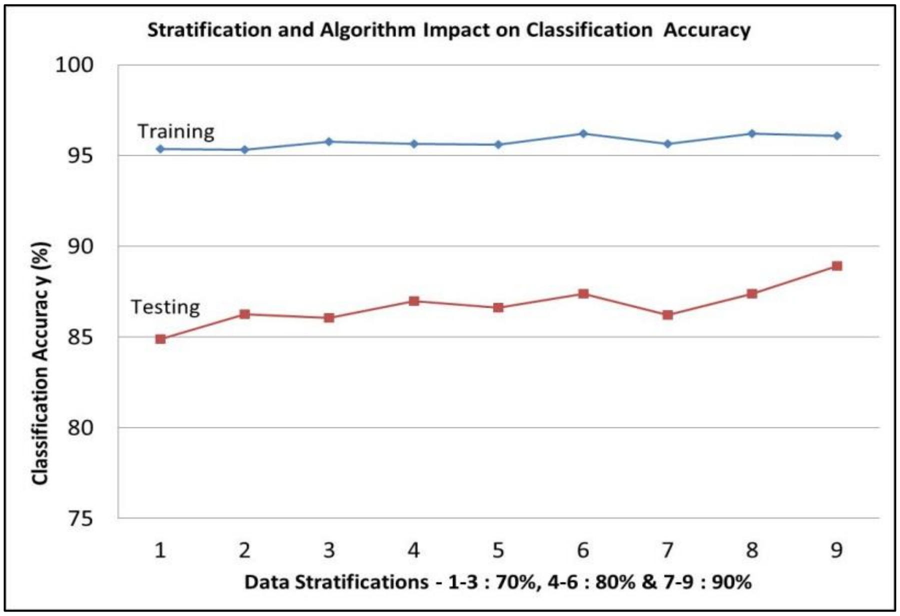

Figure 4.8: Classification accuracies — stratification levels and algorithms

D1 and D2 represent the model performance, at similar conditions, with unfiltered and filtered data, respectively. Training classification improved in the range of 1.6-2.1%. The testing classification accuracy demonstrated good improvement, which ranged from 5.3-6.2%, as can be seen in Table 4.10.

Table 4.10: Test Results after Data Cleanup at 70% Stratification

	Gini			Twoing			Deviance		
Classification	D1	D2	Improvement	D1	D2	Improvement	D1	D2	Improvement
Training (%)	95.3	97.3	2.1%	95.3	97.4	2.2%	95.7	97.2	1.6%
Testing (%)	84.9	90.2	6.2%	86.2	90.8	5.3%	86.0	90.9	5.7%

It was also observed that the different split criteria caused slight improvements in the model implementation. The number of input features and their relevancy to the problem had significant impact in this problem. This agrees with similar observations published in the fault classification problems discussed by Amarnath et al. [16] and Sugumaran et al. [21].

4.5.2 Model Validation using Real Plant Equipment

To ensure the model works with real machinery data, some data with unbalance condition were collected and used on the same model. To ensure the similar comparison, similar features and the same split criterion were used. In this analysis, we used a 70% stratification factor rather than comparing different ranges as we observed that there was no significant improvement among the stratification strategies. Table 4.11 shows the performance results of the model at different split criteria. It was observed that the model was able to generalize well with real equipment data as the features in the real plant are not controlled like in the laboratory setup. The training accuracy is comparable to that of cleaned data. Testing accuracy improved by 2.1%, 0.7% and 2.3% with the Gini, Twoing and Deviance split criteria, respectively. The Area under Curve (AUC) also slightly improved in the range of 99.7-99.9%, which shows that the model is capable of excellent generalization with real operational data.

Table 4.11: Real Plant Equipment Data Results

Classification	Gini	Twoing	Deviance
Training (%)	97.8	97.5	97.9
Testing (%)	92.3	91.5	93.4
Area Under Curve (%)	99.8	99.7	99.9

Comparison of classification accuracy was performed to show the difference between real plant data and laboratory data as shown in Figure 4.9. The plant data showed an average of 6.7% training classification improvement and around 2.3% for testing. The improvement shown in the plant data is extremely beneficial due the potential improvement by applying proposed model to real life industrial problems.

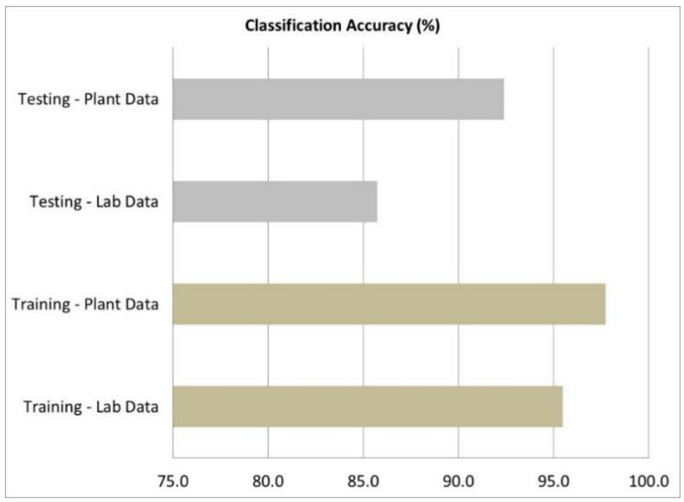

Figure 4.9: Classification accuracy comparison

The results of the fault detection accuracy using real plant data are shown in Table 4.12. Real plant machinery vibration data were used to detect unbalance fault using the DT based proposed algorithm. The model has shown that on average the model has the capability of detecting faults correctly in ranges from 98.4 - 99.4% with an incorrectly detecting a fault range from 0.53 - 1.26%. In published research [16], a DT based fault detection model was proposed using acoustic signals for fault detection. The results showed the true positive accuracy ranges from 93.3 - 96.7% and incorrect detection was around 3.3

- 6.7%. In another work presented by Sugumaran et al [21], where the vibration signals are used to detect faults, 86% of true accuracy and 14% of incorrect detection is reported. We acknowledge that there are some differences among other published works [16-17, 20, 22] and this work, such as different systems, different faults and sensors. However, the commonality is that all have used DTs based models for fault detection. Based on this commonality, the proposed model in this research delivers a true positive level that is comparable to the results reported by others utilizing similar methods.

Table 4.12: Fault detection using the proposed DT based model

Description	Fault Labeled Correctly (%)	Fault Labeled Incorrectly (%)
Average – Gini	99.47	0.53
Average – Twoing	98.44	1.56
Average – Deviance	98.74	1.26

4.6 Conclusion

Fault detection and management plays a vital role in managing system availability. An application of DTs for detecting machinery faults and addressing them through proper management action has been successfully presented. A DTs based predictive model was developed to detect faults and their severity using vibration data. The overall testing classification accuracy was about 97% and the testing accuracy was 92% has achieved, which is comparable with other DTs based fault detection models.

We observed a 5% overall improvement in the classification accuracies when filtered data were used instead of an initial noisy and unfiltered data. Results also showed significant improvements using optimal features as the training classification accuracy with 4 features is around 95% and testing classification accuracy is around 85%. The highest classification accuracy performance of 85% with 7 features and about 83% with 4 features is also reported in another work [21], which is in-line with this work finding. The model validation using real plant data compared to laboratory data was outstanding as the testing and training accuracies improved by 6.7% and 2.3%, respectively. The proposed model has shown that on average the model has the capability of detecting faults correctly in ranges from 98.4 - 99.4% with an incorrectly detecting fault range between 0.5 - 1.2%. This indeed is a great benefit for plant engineering in handling faults.

Although, this work is limited to three fault conditions, but model can be extended to dynamic online system to diagnose other machinery faults under different operating conditions. The other limitation experienced during the development of this model is changing operating conditions and possible fault scenarios in testing data. To address this limitation, we have developed the dynamic model which has capability of updating the training sets to include the new possible scenarios without building the model from scratch. The performance of the proposed model demonstrated that it can be practically used for detecting fault conditions and their severities in real and operational scenarios of rotating machines. Along with detection of faults, the proposed fault management strategy also plays an important role in enhancing plant availability. The machine learning-based holistic approach from detection to management proposed would be of great help to avoid unscheduled breakdowns and improving the availability of facilities.

CHAPTER 5

A MULTI-CONSTRAINED MAINTENANCE SCHEDULING OPTIMIZATION [5]

Abstract

A maintenance scheduling optimization model considering equipment risk, total maintenance cost, system reliability, and availability is proposed. This work is motivated by gas processing operator concern for high maintenance costs, poor availability and reliability caused by inefficient maintenance scheduling. The approach presented in this

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[5] *This Chapter is based on the published work in a peer-reviewed journal. Qadeer Ahmed, Kamran S. Moghaddam, Syed A. Raza, Faisal I. Khan (2015), "A Multi Constrained Maintenance Scheduling Optimization Model for Hydrocarbon Processing Facilities," Journal of Risk and Reliability Engineering, accepted for publication. To minimize the duplication, all the references are listed in the reference list. The contribution of the authors is presented in Section titled, "Co-authorship Statement". The contribution of the authors is presented in Section titled, "Co-authorship Statement".*

Chapter addresses the optimization of maintenance costs by efficiently scheduling maintenance tasks subject to reliability and availability constraints. Four maintenance actions are considered for equipment; namely corrective, replacement, maintenance, and inspection. The proposed solution develops maintenance schedules for complex repairable system with equipment operating in series. Two single objective, nonlinear mathematical models are presented to find the optimal maintenance cost subject to reliability and system reliability subject to availability constraint. A goal programming model is also proposed to simultaneously deal with multiple criteria based on their importance and defined goals. A gas absorption system of a hydrocarbon processing facility is used to ensure the practicality of the proposed formulation to real industry problems. A comparison of existing and proposed formulation is carried out to show that the proposed optimization approach is an efficient method for optimizing maintenance schedules and flexibility to adjust schedules in complex operating systems.

5.1 Introduction

Equipment availability and effective maintenance are two strongly related important criteria for ensuring safe operative system that is capable of handling production requirements. Proper maintenance of deteriorating equipment prevents unwanted breakdowns, which lead to poor system reliability and high production cost. Low system reliability and availability negatively impact the company’s image and commitment to deliver on-time quality products. Equipment breakdowns are unsafe and generally cost the company a huge amount of capital along with jeopardizing its reputation in industry. These issues encourage organizations to develop smarter and effective strategies to significantly improve maintenance schedules to achieve safe operations with high equipment availability and lower costs. A balance between expense and profit is also an objective for any organization to stay in business and meet the expectations of stakeholders. The benefits of maintenance schedule optimization have led researchers to develop optimization methods and techniques, which have been proposed and published over the years. The proposed methods have a wide range of objectives, constraints, and optimization methodologies with a common goal of achieving low cost and effective solutions. In general, maintenance is critical to ensure system availability, but advances in technology and new heuristic algorithms have paved new roads to efficiently optimize maintenance actions. Maintenance has become a vital function as maintenance cost is a significant portion of the total operating cost in asset intensive industries such as petrochemical and gas plants. Different types of maintenance tasks have been introduced and practiced in industry including preventive, predictive, reactive, and corrective maintenance. Realistic maintenance requirements must be properly understood and action plans should be properly developed to address the equipment failure modes. Maintenance has two critical aspects; what and when? "What" relates to a maintenance task or activity; and "when" explains the time characteristics of maintenance. Both features are critical and, if not handled correctly, can negatively impact both availability and cost. We will concentrate on maintenance scheduling optimization, which includes corrective, preventive, replacement, and inspection maintenance.

Maintenance is defined as *"a task performed to retain or restore a function of equipment during its life cycle"* [1]. Much maintenance, including preventive, corrective, reactive, operational, and others are available to ensure improved functionality of the equipment. In this research, we have considered four major maintenance tasks, namely inspection, maintenance, corrective, and replacement. Preventive maintenance can be defined as, "*a fundamental, planned maintenance activity designed to improve equipment life and avoid any unplanned maintenance activity* [1]." Preventive maintenance has a direct impact on availability necessitating selection of appropriate tasks at proper intervals. Corrective maintenance is defined as *"a maintenance task performed to repair or restore function of equipment after a breakdown."* This category of maintenance is often expensive due to the failure of multiple components in an unscheduled breakdown event [2]. Replacement maintenance is a task where the component of equipment is replaced based on the established life of components. In this maintenance activity, the cost is lower due to the prior planning of component replacement. An inspection task is defined as "*the task performed on equipment while in operation to spot any abnormality*." This task generally requires cleaning, lubrication, minor adjustment, and reporting of any abnormality found during inspection. While inspection is generally performed by plant operators; other maintenance tasks are performed by maintenance technicians and maintenance engineers. Predictive maintenance is also a maintenance activity classified as *"a technique that helps determine the condition of in-service equipment in order to predict when maintenance should be performed"* [3]. A predictive approach offers some benefits over other maintenance actions, but requires good quality data and experienced individuals to interpret the data to make correct decisions. There is a great effort in development of smart diagnostics and prognostics algorithms to enhance the prediction accuracy; but it is not part of this work.

Maintenance optimization is a very important area of research due to its potential benefits to industry. It has gained exposure as a result of significant change in traditional and contemporary maintenance, where maintenance has no longer only an organization's support function but considered as business driver. These days maintenance focus is not only to keep the plant in operation but emphasis is also on efficient utilization of equipment. Maintenance management becomes extremely important in industries such as liquefied natural gas (LNG) due to the presence of a large number and wide variety of critical equipment. Processing LNG is a hazardous process requiring considerable safety. It is a cryogenic process where the operating temperature is around -164°C and any failure can have catastrophic consequences. As a result, effective and optimized maintenance is a key to safety, optimal availability, and reduced overall maintenance cost of the facilities. Maintenance in hydrocarbon processing facilities is important not only because of critical application but also unplanned breakdown equipment cost is significant in terms of production loss and customer satisfaction by missing the promised deliveries. These are some reasons that many researchers from industry and academia are involved in the formulation of new maintenance optimization models and algorithms to address this area. Maintenance optimization has progressed through different stages as the knowledge and tools become available to solve complex problems. Advances in optimization algorithms have paved the road for solving multi-objective maintenance optimization. Earlier, maintenance optimization models were more focused on cost minimization and maintenance task schedules. This may be due to the limitation of the advanced data processing tools, i.e., computerized maintenance management systems (CMMS), asset performance management (APM) systems, efficient simulators and high speed processors, along with lack of understanding of the influence of maintenance relationships with other variables. Developments in technology and innovation have introduced processing of utilized data and data mining to understand equipment failure modes and their consequences for developing the right maintenance actions. Understanding risk and consequences of failure of equipment greatly helps in the selection of optimal execution of maintenance intervals through risk-based prioritization. Risk-based maintenance scheduling optimization can greatly influence maintenance costs as it addresses equipment criticality and prioritization of tasks accordingly. Risk is a product of probability of equipment failure and its consequence to environment, production and personnel [4]. The term, Equipment Risk Index (ERI) classifies the equipment criticality and helps to prioritize maintenance actions. This risk index ranges from high to low; a higher ERI score is used to determine the maintenance priority.

Nowadays, extensive research in maintenance scheduling optimization is being conducted due to its usefulness and benefits to industry. This includes maintenance scheduling using dynamic programming and introduction of heuristic algorithms in maintenance optimization with reliability, availability, and budget criteria [5]. In other work, integer programming and branch-and-bound was introduced. Branch-and-bound is a technique for solving integer linear programming (ILP) problems but integer programming has limitations in solving nonlinear objective functions [6]. Some other meta-heuristics, like genetic algorithms, have been introduced to effectively handle optimization problems in maintenance and reliability contexts [7-9]. A genetic algorithm (GA) is efficient in addressing nonlinearity. Most meta-heuristic algorithms are approximate and mostly non-deterministic; similarly, GAs are approximate and cannot guarantee an optimal solution. Newer research covers many areas in maintenance optimization, which includes cost, manpower, resources, operation, and equipment shutdown schedules to reap real benefit by properly optimizing maintenance tasks. In this work, different maintenance tasks are used to minimize maintenance cost subject to reliability, and maximize reliability subject to system availability. A gas absorption unit in a gas processing plant is used to implement the proposed maintenance schedule optimization.

5.1.1 Description of a Natural Gas Treatment and Gas Absorption System

A natural gas processing plant is asset intensive and demands proper care of equipment to ensure safe and continuous operation. In these asset intensive plants, proper and timely maintenance is vital to guarantee safety and meet customers' demands from around the globe by producing product on schedule. This makes maintenance scheduling and optimization an important function in process plants. Gas is produced at plants in both forms, i.e., gas and liquid. In liquid form, the temperature of natural gas is usually around -160°C and the volume is around 1/600 times that of gas at room temperature. A general gas process consists of following several major steps as shown in Figure 5.1. Raw gas is received from a reservoir to the inlet receiving area, which is followed by treatment of corrosive and hazardous contents, liquefaction of natural gas or storage, and shipping of the gas.

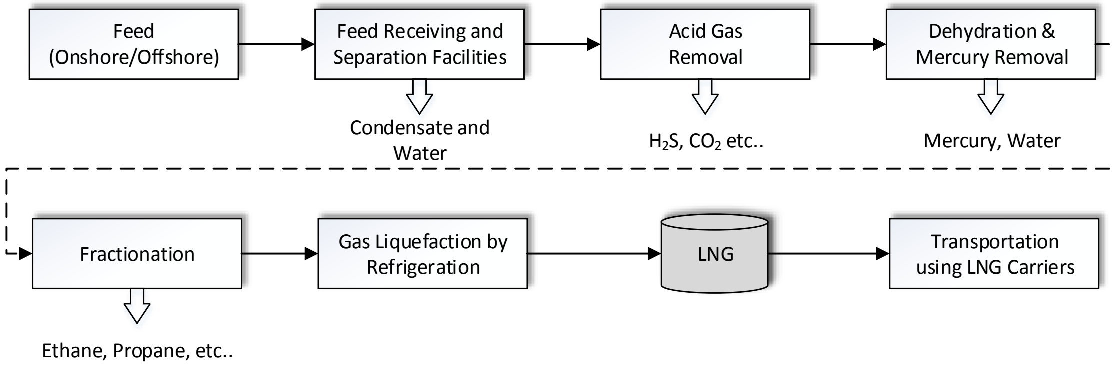

Figure 5.1: General product flow in a gas processing plant [4]

Generally, from the reservoir, a three-phase feedstock is sent to the onshore receiving area where the gas, condensate, and water are separated from feedstock. Natural gas from wells usually contains many hazardous and non-hazardous elements, which in most cases must be removed prior to NG liquefaction. These hazardous elements are usually sulfur in the form of hydrogen sulfide, carbon dioxide, water, helium, mercury, other sulfur species, and heavy hydrocarbons. They have detrimental effects on equipment and require efficient maintenance and operation to improve system availability. The natural gas feedstock is treated in gas sweetening unit to remove sulfur and water. Other contaminants like mercury and mercaptan are removed from gas prior to the other process to enhance the life of the equipment, i.e., aluminum exchangers. In this research, a Section of a gas sweetening unit in a gas processing plant is selected to optimize maintenance schedule under constraints. It mainly consists of acid gas removal from the gas stream. The absorption unit is very critical for both safety and production as it absorbs hydrogen sulfide and carbon dioxide. These gases are highly corrosive and will cause severe damage to cryogenic vessels during the liquefaction process; therefore, it is necessary to remove these gases and contaminants before they reach the final stages of liquefaction. In the acid gas absorbers, hydrogen sulfide and carbon dioxide gases are absorbed completely in the solvent and sweet natural gas is routed to the gas drying Section and liquefaction units. Since the natural gas sweetening process is very critical in terms of operations and commitment needed for production, the availability and reliability of all the equipment remains under focus and operational integrity is monitored closely. For reliable processing of the gas sweetening unit, all required equipment must be maintained for overall operation of the plant.

5.1.2 Research Objective and Contributions

While maintenance is one of the important activities in processing facilities; it should not be taken as an inevitable source of cost savings to ensure continuous and safe operation. The importance of maintenance management and optimization is reflected in many publications by researchers, as discussed in Section 5.2 of this Chapter. We have addressed optimal maintenance scheduling in a gas absorption system of a natural gas processing plant where maintenance is critical and extremely important due to the risk posed by high gas pressure, low operating temperatures, and the presence of hazardous hydrocarbons. We expanded previous work by developing a framework and mathematical formulation that is applicable to repairable systems using four different maintenance actions of inspection, preventive, corrective, and replacement [5]. Corrective maintenance action due to equipment breakdown is also considered, which can negatively impact availability, reliability, and safe work environment. The advantages offered by optimal maintenance scheduling are two-fold; it minimizes maintenance durations to ensure plant availability and directs optimum maintenance scheduling actions to keep the maintenance cost low for a desired level of availability and reliability. This work mainly presents four major contributions, which are:

1. Developed two single objective optimization models, (1) minimization of maintenance cost subject to reliability constraints, and (2) maximization of system reliability subject to availability constraints.
2. Developed a goal programming model that simultaneously considers multiple criteria; cost, reliability, and availability. This model was applied on a gas absorption system using different goals and weights to obtain Pareto-optimal maintenance schedules to demonstrate the formulation applicability to real industry problems.
3. Maintenance costs, maintenance duration, system reliability, and availability of an existing gas absorption system were estimated to compare with proposed formulation results.
4. Introduced the concept of the ERI while handling real plant maintenance prioritization. The ERI is used to classify equipment criticality, which helps with prioritizing the maintenance task particularly during a resource or schedule

constraint. The effect of the ERI on maintenance schedules is presented in Section 5.3.2.

This work proposes a maintenance scheduling optimization approach that minimizes maintenance costs subject to desired plant reliability and availability targets. Section 5.1 provides the introduction of maintenance, maintenance optimization, and a brief description of a gas absorption system; and Section 5.2 provides the literature survey. Section 5.3 encompasses the problem formulation and constraint development. In Section 5.4, three optimization models are developed. In Section 5.5, an analysis of the proposed models is carried out. Section 5.6 presents the results of developed model when applied to a gas absorption system and maintenance cost comparison is performed using the existing maintenance practices. Finally, in Section 5.7 the results are summarized in a conclusion.

5.2 Literature Research

Maintenance and reliability optimization have been investigated by many researchers for the last couple of decades. In general, optimization is a mathematical model to find the best or optimal solution from all possible solutions. These models have been developed to optimize different objective functions, including but not limited to, revenues, maintenance schedules, system availability, and costs in different industries. In this work, we are focused on maintenance scheduling optimization of a processing facility, and so some related work is explored. Several optimization techniques in single objective optimization have been introduced, and now researchers are more focused on multi-objective optimization due to its extensive application and utilization in real life applications. A single-objective optimization problem in which more than one criterion is considered simultaneously becomes multi-objective optimization [10]. Maintenance is important to ensure availability and manage maintenance cost, which makes it an interesting area of research both from an academia and industry perspective.

In this Section, we have discussed the work performed in the area of maintenance schedule optimization. Maintenance optimization in hydrocarbon facilities is not explored extensively, which provides an opportunity to expand in this area. A joint production and maintenance scheduling model with multiple preventive maintenance services is presented [11]. To handle this problem, a mixed integer nonlinear programming model is developed and then a population-based variable neighborhood search algorithm is devised for a solution method. The simulation outcome shows the outstanding performance of traditional genetic algorithms and basic variable neighborhood search in terms of both effectiveness and robustness. A cost minimization objective function with system reliability is presented to optimize the maintenance schedule [12]. A component-based heuristic algorithm was developed to solve the optimization model for a real field system while maintaining the architecture or components in a traction catenary system. A meta-heuristic model is presented for maintenance scheduling of generators using hybrid improved binary particle swarm optimization based coordinated deterministic and stochastic approach [13]. The objective function focuses on reducing the loss of load probability and minimizing the annual supply reserve ratio deviation for a power system as a measure of power system reliability. The proposed method yields better results by improving search performance and better convergence characteristics compared to the other optimization methods and conventional method. A technique based on one of the artificial immune system techniques known as the clonal selection algorithm to obtain the optimal maintenance schedule outage of generating units is proposed [14]. It has successfully been used to solve the maintenance scheduling sub-problem to obtain the optimal maintenance outage of each unit.

Risk is a critical component in decision making processes and plays a vital role in maintenance optimization. Risk-based optimizations are also gaining momentum to explore the detrimental effects of equipment breakdowns on the operation of processing facilities. These effects cover production revenue loss, downtime, environmental, and safety concerns due to the unavailability of equipment. Many researchers have worked on risk-based approaches to maintenance optimizations [15-17]. A risk-based optimization model for system maintenance scheduling problems is proposed, which consists of optimizing availability and the cost of the system by balancing between system maintenance risk and failure risk [18]. A genetic algorithm is used to obtain the sequence of maintenance actions providing a desired level of reliability with minimum system risk. Results obtained from the modeling approach support the validity of the model in optimizing maintenance schedules. A new version of the simulated annealing method for solving the generator maintenance scheduling problem is presented [19]. The model considered in this paper is formulated as a mixed integer program, with a reliability optimality criterion, subject to a number of constraints. The proposed simulated annealing algorithm performs very well compared to other methods on the benchmark test system presented in literature. A preventive maintenance scheduling problem with interval costs to schedule preventive maintenance of the components is proposed [20]. A study is performed from a polyhedral and exact solution point of view, as opposed to previously studied heuristics. As a result, the proposed model can be effectively used as a building block to model several types of maintenance planning problems possessing deterioration costs. A hybrid evolutionary algorithm is explored to tackle the reliability based generator maintenance scheduling problem [21]. Uncertainties in the generating units and the load variations are included so that a more realistic scheduling is obtained. A new local search method, which is derived from external optimization and genetic algorithm, is presented to tackle the problem. This method can be used as a local optimizer to further improve the potential solutions in the genetic algorithm. An advanced progressive real coded genetic algorithm is applied to optimize the availability of standby systems with preventive maintenance scheduling [22]. Results from an emergency system are compared with those obtained by some standard maintenance policies, and previously published papers.

A modified genetic algorithm approach to long-term generation maintenance scheduling to enhance the reliability of the units is presented [23]. Maintenance scheduling establishes the outage time scheduling of units in a particular time horizon. The proposed methodology is used for finding the optimum preventive maintenance scheduling of generating units in power system. The objective function is to maintain the utility power system units as early as possible under constrains such as spinning reserve, duration of maintenance and maintenance crew are being taken into account. A selection of multiple maintenance strategy in process equipment is presented [24]. Three maintenance strategies namely, repair maintenance, preventive maintenance, and preventive replacement on equipment reliability was analyzed. The harmony search algorithm was designed to solve the model, and the diversity of solutions was ensured by generating the new solution and the replacement process. A non-dominated sorting genetic algorithm based optimization approach is presented for an optimum maintenance to improve the average reliability of ship's operations at sea at minimum cost [25]. The advantages are explored that can accrue from introducing short maintenance periods for a select group of machinery, within the constraints of mandatory operational time, over the method of following a common maintenance interval for all the machinery. An integrated model for the joint determination of both optimal inspection strategy and optimal repair policy is discussed for a manufacturing system whose resulting output is subject to system state [26]. In this paper, an intensity control model adapted to partial information provides an optimal inspection intensity and repair degree of the system as an optimal control process to yield maximum revenue. A numerical example is provided to illustrate the behavior of the optimal control process. An inspection and replacement policy for a protection system is described in which the inspection process is subject to error, and false positives and false negatives are possible [27]. Two models are developed, one in which a false positive implies renewal of the protection system and the other does not implies renewal. The model allows situations in which maintenance quality differs between alternative maintainers to be investigated. Reliability is one of the most efficient and important method to study safe operation probability of hydraulic systems. The reliability of a hydraulic system of four rotary drilling machines has been analyzed [28]. The data analysis shows that the time between failures of two machines obey the Weibull distribution. Also, the time between failures of two other machines obey the lognormal distribution. Later, preventive reliability-based maintenance time intervals for 80% reliability levels for machines are presented.

The problem of determining operations and maintenance schedules for a containership equipped with various subsystems is studied during its sailing according to a predetermined navigation schedule [29]. A mixed integer programming model is developed. Then, due to the complexity of the problem, a heuristic algorithm that minimizes the sum of earliness and tardiness between the due date and the actual start time for each maintenance activity is discussed and improvement is reported over the experience based conventional method. A novel cost-reliability model, which allows the use of a flexible interval between maintenance interventions, is proposed [30]. It allows a continuous fitting of the schedules to deal with the changing failure rates of the components. A single objective optimization model was explored to determine the optimal maintenance policy by minimizing cost and respecting availability constraint for a series-parallel system [31]. In [32], an overview and tutorial about multi-objective formulation is explored. Another work proposed a multi-objective maintenance problem in relation to a system that needs to operate without interruption between two consecutive stops with a reliability level not lower than a fixed value. [33]. A multi-objective formulation is proposed to minimize the cost and maximize the availability of a global system [34]. In this proposed model, availability allocation to a repairable system at the design level is considered rather than availability in the operating phase.

The complex landscape of maintenance optimization and its huge impact on industry has received considerable attention among academia and industry to come up with methods to develop efficient maintenance schedules. In this work, we have explored the concept of equipment failure risk in maintenance by identifying critical equipment using risk assessment. Goal programming is an extension of linear programming, which provides flexibility to handle a decision concerning multiple and conflicting goals [35]. This approach is extensively applied in optimization research. Due to its handling of multiple criteria simultaneously, we have used goal programming to solve a model to study the impact of cost, reliability, and availability based on defined goals and weights. Under different goals and weights, a developed model was applied to a gas absorption system to obtain optimized maintenance schedules. To the author's knowledge, maintenance scheduling optimization has a great research potential because of the complexity of equipment failure patterns, resource availability, risk to production and society, etc. All these constraints, i.e., maintenance factor, reliability, and availability have the potential to explore and provide a great value to industry by developing maintenance strategies and optimizing them. As a result, this work is expected to contribute by developing a practical solution to the industry's concern for efficient maintenance scheduling.

5.3 Formulation of a Maintenance Optimization Model

Effective maintenance is one of the key functional areas in industry to address plant uptime, maintenance cost, safety, and availability. To address these objectives, maintenance optimization has gained momentum in understanding equipment failure modes, equipment age, remaining useful life, and the disadvantages of only performing time-based maintenance. The estimation of equipment age is a difficult task, which drives conservative maintenance schedules to avoid unscheduled breakdowns. This results in performing maintenance too early when it is not required and possibly introducing the effect of poor workmanship. If the maintenance is performed too late, equipment may run the risk of an unscheduled breakdown. This all makes maintenance scheduling a demanding area of interest for the industry and researcher. A maintenance schedule optimization is developed to minimize cost subject to system reliability and availability constraints.

Notation

A. Sets

M	Number of equipment
T	Number of intervals over the planning horizon

B. Indexes

m	Index for an equipment, $\forall\, m = \{1,2,3, \dots, M\}$
t	Index for time period, $\forall\, t = \{1,2,3, \dots, T\}$

C. Parameters

L	Length of the planning horizon
TC	Total cost
CF_m	Cost of corrective (failure) task of equipment, m
CR_m	Cost of replacement of components in equipment, m

CM_m	Cost of maintenance of equipment, m
CI_m	Cost of inspection of equipment, m
CO_m	Cost of operation task of equipment, m
CMT_m	Cost of the material of equipment, m
CLF_m	Labor cost/hour to perform a corrective task for equipment, m
CLR_m	Labor cost/hour to perform a replacement task for equipment, m
CLM_m	Labor cost/hour to perform a maintenance task for equipment, m
CLI_m	Labor cost/hour to perform an inspection task for equipment, m
ρ_m	Failure cost factor for equipment, m
TF_m	Time required to perform a corrective repair for equipment, m
TR_m	Time required to replacement equipment, m
TM_m	Time required to perform maintenance on equipment, m
TI_m	Time required to inspect equipment, m
β_m	Shape parameter of equipment, m
λ_m	Scale parameter of equipment, m
α_m	Improvement factor of equipment, m
ν_m	Rate of occurrence of failure (ROCOF)
$E[N_{mt}]$	Expected number of failures of equipment, m, and time, t
ERI_m	Equipment Risk Index of equipment, m
UB	Upper bound
LB	Lower bound
R_{mt}	Reliability of equipment, m, at time, t
A_{mt}	Availability of equipment, m, at time, t
R_{target}	Required reliability of a complete system
A_{target}	Required availability of a complete system

D. Decision variables

AS_{mt} Age of equipment, m, at the start of period, t

AE_{mt} Age of equipment, m, at the end of period, t

X_{mt} $\begin{cases} 1 & Maintenance\ task\ is\ performed\ for\ equipment, m, at\ period, t \\ 0 & Otherwise \end{cases}$

Y_{mt} $\begin{cases} 1 & Replacement\ task\ is\ performed\ for\ equipment, m, at\ period, t \\ 0 & Otherwise \end{cases}$

Z_{mt} $\begin{cases} 1 & Inspection\ task\ is\ performed\ for\ equipment, m, at\ period, t \\ 0 & Otherwise \end{cases}$

5.3.1 Maintenance Task Description

Many maintenance tasks have been developed to ensure the functionality of equipment by properly capturing their failure modes and assigning suitable tasks. In this Section, discussion will be about the mathematical formulation of the maintenance models.

5.3.1.1 Failure Model

In general, manufacturing and chemical processing plants have two types of equipment; they are classified as repairable and non-repairable. Repairable systems are subject to repair after a breakdown or failure, whereas non-repairable systems and components are replaced with similar or improved design upon failure. Weibull distribution is commonly used to model the time-to-failure of non-repairable systems; but for repairable systems, the time to failure events are not independent from each other. A non-homogeneous Poisson process (NHPP) is used to model time-dependent random failures. The system used for this type of optimization problem includes a repairable system consisting of equipment, M, subject to failure, repair, replacement, and inspection where equipment time to failure follows the NHPP. Each piece of equipment in the system is assumed to have an increasing failure rate, which suggests a shape parameter to be greater than 1. A shape parameter less than 1 represents a decreasing failure rate, and when equal to 1 the parameter corresponds to a constant failure rate. Maintenance and repair actions restore the function of equipment; as a result, we have modeled the occurrence of the failure using a stochastic non-homogeneous Poisson process. In a non-homogeneous Poisson process, failure rate is function of time. As we are considering increasing failure rate, Rate of Occurrence of Failure (ROCOF), $\nu_m(t)$ is given by [5],

$$\nu_m(t) = \lambda_m . \beta_m . t^{(\beta_m - 1)}, \qquad \forall\, m = 1, \dots, M \tag{5.1}$$

One of the objectives of this work is to develop a schedule that is generally understood as an inspection task, preventive maintenance, and a replacement or failure repair task for each equipment item, m, for a planning horizon, L. The overall planning horizon has equally spaced periods, i.e., L/T. At the end of each period, the system is evaluated, and a maintenance task or replacement task, or least inspection task, is performed. Under these conditions, if the maintenance task or repair task is performed, the inspection task should not be performed as it has taken place during other tasks. In a real-world experience, we observed that an inspection task is usually carried out even when a maintenance task is just performed, which is considered to be a non-value-added cost and burden to the operators. To evaluate the age and condition of the equipment, it is assumed that the age at the beginning of the period, t, is denoted by AS_{mt} and the end of period is denoted by AE_{mt}. From this assumption, we can write for an equipment item, m, and period, t.

$$AE_{mt} = AS_{mt} + \frac{L}{T}, \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots, T \tag{5.2}$$

Using Equation 5.1, an expected number of failures can be expressed as:

$$E[N_{mt}] = \int_{AS_{mt}}^{AE_{mt}} \nu_m\,(t)dt, \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots T \tag{5.3}$$

$$E[N_{mt}] = \int_{AS_{mt}}^{AE_{mt}} \lambda_m . \beta_m\, .\, t^{\beta_m - 1}\, dt, \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots T \tag{5.4}$$

$$E[N_{mt}] = \lambda_m\,(AE_{mt})^{\beta_m} - \lambda_m\,(AS_{mt})^{\beta_m}\,, \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots T \tag{5.5}$$

In minimization of a cost model, we have considered time to carry out maintenance or repair activity compared to the total period, which is significant in some repairs. Four different tasks are commonly used in industry. Following are explanations of the different tasks and the contexts in which they are being used in this work. The overall maintenance types are presented in Figure 5.2.

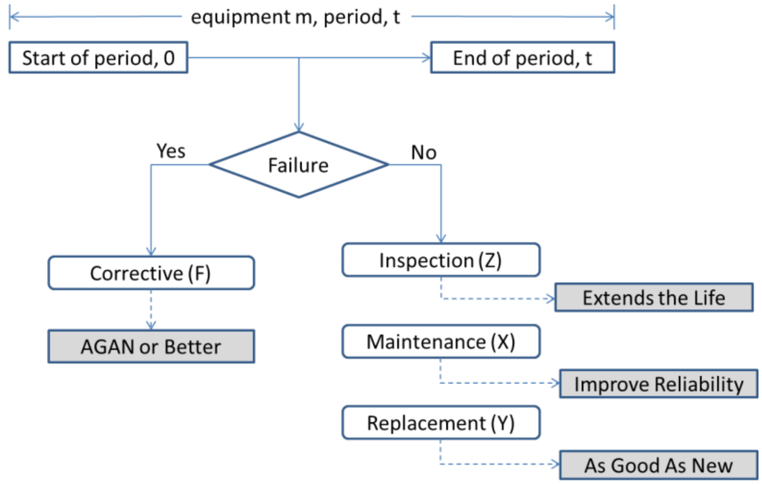

Figure 5.2: Maintenance types in a time period

5.3.1.2 Corrective Task

Corrective maintenance tasks correspond to the activities where a random failure is experienced while the system is operational. The maintenance terms used have different meanings; *correction task* and *replacement task*. A corrective action corresponds to the activities when a random failure is experienced while the system is in operation. In this case, the cost is significant and usually at least three to four time of the preventive repair and this is one of the reasons to perform appropriate maintenance to avoid such failures [2]. This corrective repair action will bring the system back to good-as-new condition or even better provided an improved technology or robust material is used in components for the corrective repair. In case of a random failure, failure investigation is mostly performed to understand the root cause of a failure, and in certain cases improved design or material is suggested to make the equipment as good as new or even better. If a failure occurred in a period, t, the age of the equipment at the start of next period, $t+1$, be considered as new, as shown in Equation 5.6.

$$AS_{m,t+1} = 0 , \qquad \forall\, m = 1, \dots , M ; t = 1, \dots T \tag{5.6}$$

Corrective cost is a function of repair time, man-hour, material cost and a failure cost factor, ρ_m. The failure cost factor (ρ_m) allows for the capture of cost impact due to an equipment breakdown. In a real plant equipment breakdown situation, we have observed that the corrective cost is higher than other non-breakdown maintenance events. This difference in cost is captured in the model by introducing a factor, ρ_m, which increases the repair cost and brings it closer to real plant maintenance cost. This factor depends upon different critical parameters, i.e., equipment history, size, crew usage, and production lost. We estimated this factor using the above parameters for each piece of equipment. The difference in ρ_m is justified by the variation in different parameters for each equipment item. Mathematically, this can be written as:

$$CF_m = \rho_m \times CR_m, \qquad \forall\, m = 1, \dots , M \tag{5.7}$$

$$CF_m = \rho_m (TF_m \times CLF_m + CMT_m), \qquad \forall\, m = 1, \dots , M \tag{5.8}$$

As the cost of material does not have an impact on schedule, to make it simple, material cost is removed from Equation 5.8, which becomes:

$$CF_m = \rho_m (TF_m \times CLF_m), \qquad \forall\, m = 1, \dots , M \tag{5.9}$$

5.3.1.3 Inspection Task

Inspection task and operator task are synonymously used in industry. It is referred to the task where plant operators evaluate the condition of the equipment by visual inspection and take appropriate action during the daily routine rounds. The earlier concept of a "do-nothing" operator is fading even with the availability of predictive technologies such as condition monitoring tools. In reality, this maintenance activity provides plant operations with the confidence that the equipment is running in an acceptable condition. This task does not significantly improve the condition of equipment but rather helps avoid faster degradation of the equipment as shown in Figure 5.3. The conceptual background of this approach is adopted from a similar concept for failure rate by Moghaddam and Usher [5]. We have extended the concept to reliability under different maintenance actions. During the inspection phase, a slight change in reliability occurs due to the equipment time in service. Reliability depends on the time and failure rate, so by performing inspection and some minor tasks we maintained the equipment condition, although there was a slight change in reliability due to the effect of aging. In conclusion, inspection helps keep machines in a reliable running condition over a long time period. For example, if an operator notices an abnormal sound from equipment, a necessary action will be taken as soon as possible by the operator, such as topping up the grease in a bearing or tightening a bolt. Similarly, if an operator sees a slight leak, an action can be taken to avoid machine failure and degradation caused by insufficient lubrication. There is minimal physical work performed on the system, but the benefits are considerable both in terms of cost and equipment life. Due to this reason, most of the companies have added such tasks in operator rounds. In this task, operators visit the site to observe operating parameter readings and abnormalities, along with routine checks and actions like adding oil and topping up water. In certain cases, they perform the activity and, where required, they notify the maintenance personnel to perform work using a maintenance crew. As discussed, inspection tasks improve the degradation mechanism of equipment but do not improve the failure rate. As we see no or minimal effect on reliability, each inspection task is associated with a fixed cost CI_m regardless the condition of the equipment. Mathematically, this can be represented as

$$AS_{mt+1} = AE_{mt}, \qquad \forall\, m = 1, \ldots, M\,; t = 1, \ldots T \tag{5.10}$$

$$v_m(AS_{mt+1}) = v_m(AE_{mt}), \qquad \forall\, m = 1, \ldots, M\,; t = 1, \ldots T \tag{5.11}$$

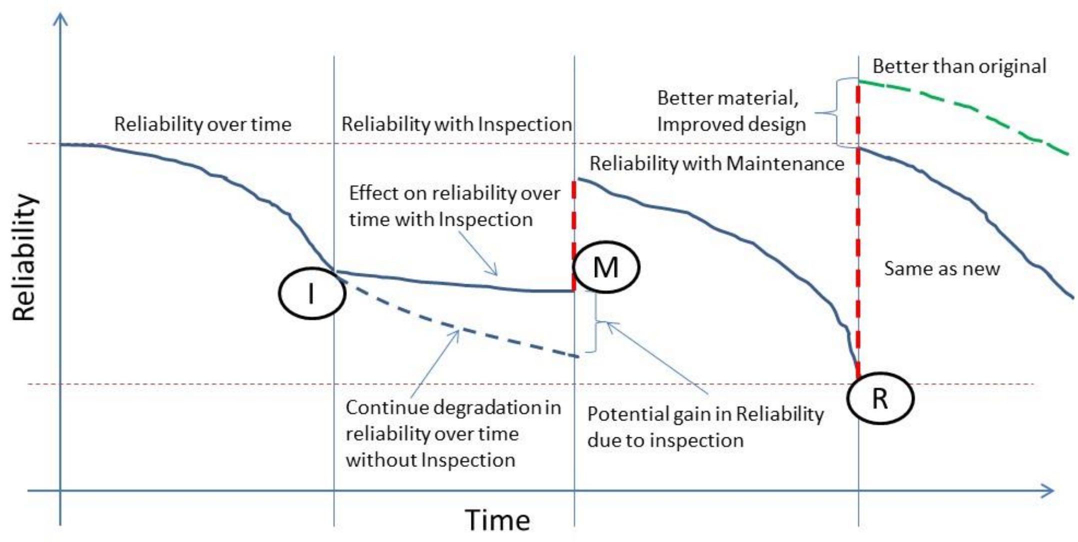

Figure 5.3: Conceptual effect on reliability under different maintenance tasks

As discussed earlier, an inspection task improves the degradation mechanism of equipment and extends the useful life of equipment, which can be written mathematically as follows:

$$CI_m = (TI_m \times CLI_m), \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots T \tag{5.12}$$

5.3.1.4 Maintenance Tasks

Under certain conditions, preventive maintenance is required to ensure smooth operation of equipment to improve the overall availability and reliability of the plant. In this research, maintenance and preventive maintenance is synonymously used, which helps to improve the condition for future periods. Preventive maintenance improves conditions, but it can also negatively influence the condition of equipment because of improper maintenance. To include the impact of maintenance on the condition of the equipment, a term α is introduced [5]. Maintenance action during a period, t, improves the failure rate. The value of α ranges from 0 to 1; with 0 indicating that maintenance brought the equipment back to "good-as-new" condition and 1 indicating that the equipment condition is as "bad-as-old." The effect of maintenance tasks on the condition of the equipment can be written as follows:

$$AS_{mt+1} = \alpha_m . AE_{mt}, \qquad \forall\, m = 1, \dots, M\,; t = 1, \dots T \tag{5.13}$$

The maintenance cost of an activity can be written as follows:

$$CM_m = \ (TM_m \ \times CLM_m), \qquad \forall \, m = 1, \dots, M \, ; t = 1, \dots T \tag{5.14}$$

5.3.1.5 Replacement Task

One of the maintenance actions to ensure equipment reliability and availability throughout the equipment life-cycle is replacement tasks. In a replacement task, the equipment is refurbished or completely overhauled during a period of time, t, and the system is considered as “good-as-new.” This replacement task is required to avoid catastrophic random failures where the component of equipment is operating in a wear-out region. All degraded components, like seals, bearings, and other major components are replaced with new and improved components. The replacement is based on the historical estimated life of the component or can be identified using condition monitoring techniques, i.e., lubrication analysis, vibration data analysis, etc. In the real world, this replacement activity is sometimes performed under the domain of opportunistic maintenance; for example, if there is a planned shutdown of a processing unit, this task can be performed to avoid the risk of failure during normal operation based on the condition of equipment. The replacement task brings the equipment back to new condition or even improves the condition where existing components have been replaced with new improved design or material for the next period. For example, if a repair is performed at the end of a period, t, the system is considered new for the next period, $t + 1$.

$$AS_{mt+1} = 0, \qquad \forall \, m = 1, \dots, M \, ; t = 1, \dots T \tag{5.15}$$

Replacement cost can be estimated using Equation 5.17; while the material cost is independent of the maintenance schedule so we take it out for schedule optimization, per the following formula:

$$CR_m = (TR_m \times CLR_m + CMT_m), \qquad \forall\, m = 1, \dots, M \tag{5.16}$$

$$CR_m = (TR_m \times CLR_m), \qquad \forall\, m = 1, \dots, M \tag{5.17}$$

5.3.2 Equipment Risk Index (ERI)

The Equipment Risk Index is a quantitative measure to estimate the importance or criticality of equipment in an operating plant. Many qualitative and quantitative methods are available to define and establish risk. The risk in general is the probability of an event and its consequence as suggested in Equation 5.18. The consequences can be classified based on different categories, which are considered important in a business such as safety and health, production lost, and the operating history of the equipment. In this work, the main objective of risk categorization is to establish an ERI, which can be used as a basis to prioritize maintenance.

$$Equipment\ Risk\ Index = Probability\ of\ Failure\ \times Consequence \tag{5.18}$$

The risk categorization also helps to give due importance to equipment, prioritization of maintenance work, managing spare parts, and other related activities. A similar concept has been used in an earlier work [4] to establish equipment risk, but that was mainly to simplify the system based on equipment criticality. In this work, ERI is more useful in maintenance prioritization. In general, there are three categories of risk, which are high, medium and low. The ERI can be effectively used to prioritize maintenance based on the equipment unavailability consequences rather than handling them with some other criteria.

5.3.3 Formulation of Reliability Constraint

The objective in this formulation is minimizing cost by optimizing the maintenance schedule and ensuring a certain level of system reliability is achieved. The system under study is an absorption system in a gas plant and equipment are operating in series. The system contains the static equipment, i.e., vessels and columns and rotating machines. The scope of this problem formulation is based on optimization of the maintenance schedule for rotating equipment and motorized valves. Static equipment is generally subject to regulatory compliance for inspection where optimization can suggest violation of regulatory requirements and guidelines. To develop the system reliability constraint, we have assumed the failure follows increasing failure pattern. As discussed earlier, the rate of failure of occurrence for repairable a system follows NHPP, so the failure rate is replaced with ROCOF. The formulation of system reliability is presented as,

$$R_{mt} = e^{-E[N_{mt}]} \ , \qquad \forall\, m = 1, \dots, M\, ;\, t = 1, \dots T \tag{5.19}$$

where, the failure rate is replaced with the ROCOF function,

$$R_{mt} = e^{-\left(\int_{AS_{mt}}^{AE_{mt}} v_m(t)dt\right)} , \qquad \forall\, m = 1, \dots, M \,; t = 1, \dots T \tag{5.20}$$

$$R_{mt} = e^{-\left(\lambda_m\, (AE_{mt})^{\beta m} - \lambda_m\, (AS_{mt})^{\beta m}\right)}, \qquad \forall\, m = 1, \dots, M \,; t = 1, \dots T \tag{5.21}$$

For a system in series, reliability is given by,

$$R_{system} = \prod_{m=1}^{M} \prod_{t=1}^{T} e^{-\left(\lambda_m\, (AE_{mt})^{\beta m} - \lambda_m\, (AS_{mt})^{\beta m}\right)} \tag{5.22}$$

5.3.4 Formulation of Availability Constraint

Availability is a probability that a system is available when required to provide a function and indeed a key requirement. One of the other objectives of this model is to develop an optimized reliability model subject to availability constraint. Availability is a function of failure rate and repair rate. If the equipment is not maintained properly, its unavailability increases over time due to increasing failure rate. Second, availability is also affected by the schedule maintenance activities so it is desired to optimize the schedule downtime as well to ensure the equipment is available. Mathematically, system availability for equipment and a series system can be written as,

$$A = \frac{Uptime}{Uptime + Downtime} \tag{5.23}$$

$$A_{mt} = \frac{AE_{mt} - AS_{mt}}{(AE_{mt} - AS_{mt}) + Downtime}, \qquad \forall\; m = 1, \dots, M \,; t = 1, \dots T \tag{5.24}$$

$$A_{mt} = \frac{AE_{mt} - AS_{mt}}{(AE_{mt} - AS_{mt}) + TF_m[\lambda_m\,(AE_{mt})^{\beta_m} - \lambda_m\,(AS_{mt})^{\beta_m}] + (TM_m.X_{mt} + TR_m.Y_{mt})}, \quad (5.25)$$

$$\forall\ m = 1, \dots, M\,;\, t = 1, \dots T$$

$$A_{system} = \prod_{m=1}^{M}\prod_{t=1}^{T}\left[\frac{AE_{mt} - AS_{mt}}{(AE_{mt} - AS_{mt}) + TF_m[\lambda_m\,(AE_{mt})^{\beta_m} - \lambda_m\left(AS_{mt}\right)^{\beta_m}] + (TM_m.X_{mt} + TR_m.Y_{mt})}\right] \quad (5.26)$$

5.4 Optimization Models

In this Section, three maintenance scheduling optimization models are developed. The objective function of the first model is to minimize maintenance cost subject to reliability constraints. The second model explores the maximization of reliability subject to system availability constraints. The last model is based on goal programming where the multiple criteria are used to develop maintenance schedules and the effect of weights under different goals was observed. All pieces of equipment are in series, and a model is developed based on the series system as shown in Figure 5.4. Details of each model are given in the respective Sections.

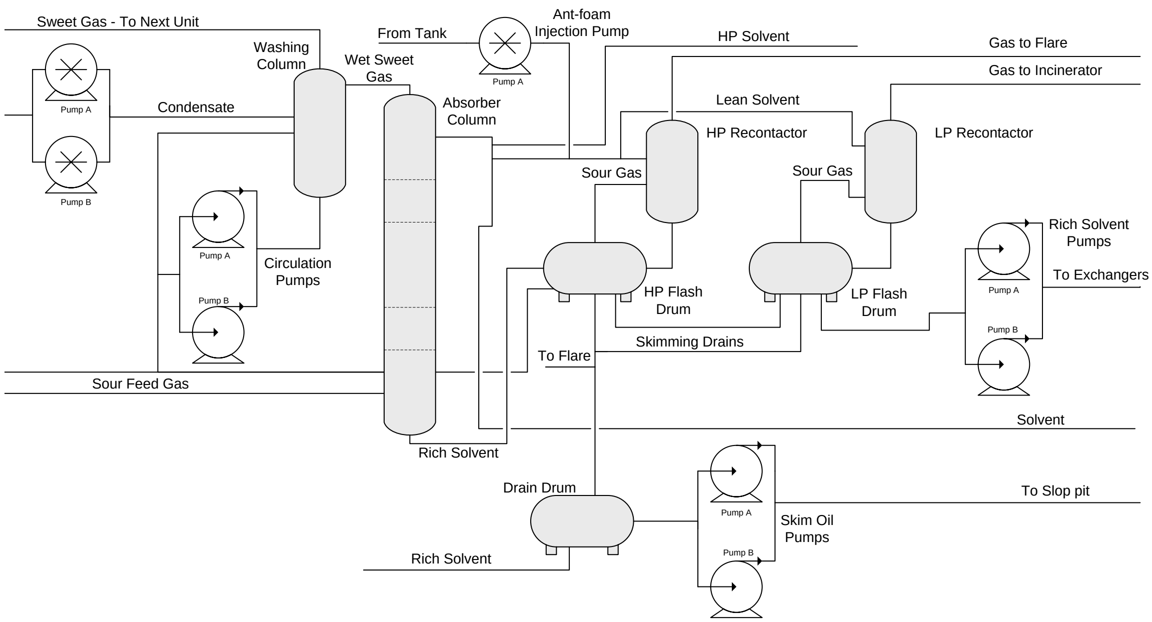

Figure 5.4: Overall Schematic of a Gas Absorption System [4]

5.4.1 Minimize Total Maintenance Cost subject to Reliability Constraints

In this optimization model, the objective is to minimize cost by optimizing the maintenance schedule based on the condition or age of the equipment and ensure that the plant meets the required reliability targets. All the equipment items are in series, and the model is developed based on the series as shown in Figure 5.4. Formulation of the total cost model is subject to the reliability constraints given below:

$Minimize\ Total\ Cost$

$$= \sum_{m=1}^{M} \sum_{t=1}^{T} [Failure\ Cost + Maintenance\ Cost] \tag{5.27}$$

$$= \sum_{m=1}^{M} \sum_{t=1}^{T} [CF_m . E[N_{mt}] + \{(CM_m . X_{mt}) + (CR_m . Y_{mt}) + (CI_m . Z_{mt})\}]$$

$Subject\ to$:

$$AS_{m1} = 0, \qquad \forall\, m = 1, \dots, M \tag{5.28}$$

$$AS_{mt} = (AE_{mt-1})Z_{mt} + (\alpha_m . AE_{mt-1}) . X_{mt}, \qquad \forall\, m = 1, \dots, M\ ; t = 2, \dots T \tag{5.29}$$

$$AE_{mt} = AS_{mt} + \frac{L}{T}, \qquad \forall\, m = 1, \dots, M\ ; t = 1, \dots T \tag{5.30}$$

$$\prod_{m=1}^{M} \prod_{t=1}^{T} e^{-\left(\lambda_m\, (AE_{mt})^{\beta m} - \lambda_m\, (AS_{mt})^{\beta m}\right)} \geq R_{target} \tag{5.31}$$

$$X_{mt} + Y_{mt} + Z_{mt} = 1 \tag{5.32}$$

$$AS_{mt}, AE_{mt} \geq 0 \tag{5.33}$$

$$X_{mt}, Y_{mt}, Z_{mt} = \{0, 1\} \tag{5.34}$$

5.4.2 Maximize System Reliability subject to Availability Constraints

In this optimization model, the objective is to maximize reliability subject to availability targets. All the equipment items are in series, and the model is developed based on the series shown in Figure 5.4. Formulation of the maximization of reliability is subject to the availability constraint given below:

$$Maximize\ Reliability = \prod_{m=1}^{M} \prod_{t=1}^{T} e^{-\left(\lambda_m\, (AE_{mt})^{\beta m} - \lambda_m\, (AS_{mt})^{\beta m}\right)} \tag{5.35}$$

$Subject\ to$:

$$AS_{m1} = 0, \qquad \forall\, m = 1, \dots, M \tag{5.36}$$

$$AS_{mt} = (AE_{mt-1})Z_{mt} + (\alpha_m . AE_{mt-1}).X_{mt}, \qquad \forall\, m = 1, \dots, M\, ; t = 2, \dots T \tag{5.37}$$

$$AE_{mt} = AS_{mt} + \frac{L}{T}, \qquad \forall\, m = 1, \dots, M\, ; t = 1, \dots T \tag{5.38}$$

$$\prod_{m=1}^{M} \prod_{t=1}^{T} \left[\frac{AE_{mt} - AS_{mt}}{(AE_{mt} - AS_{mt}) + TF_m[\lambda_m\, (AE_{mt})^{\beta_m} - \lambda_m \left(AS_{mt}\right)^{\beta_m}] + (TM_m . X_{mt} + TR_m . Y_{mt})} \right] \geq A_{target} \tag{5.39}$$

$$X_{mt} + Y_{mt} + Z_{mt} = 1 \tag{5.40}$$

$$AS_{mt}, AE_{mt} \geq 0 \tag{5.41}$$

$$X_{mt}, Y_{mt}, Z_{mt} = \{0, 1\} \tag{5.42}$$

5.4.3 Minimization of Deviation from Goals using Goal Programming

Goal programming is an effective tool in multi-criteria decision making. It is an extension of linear programming to handle multiple optimization objectives. It is an optimization program and works with a given target value and importance to the decision variables. Deviations are minimized from goals using an achievement function. All three criteria were used with different goals and weights to come up with strategies. Formulation of the goal programming objective function, which is minimization of summation of deviation from designated goals, is given below:

$$Minimize\ weighted\ deviations\ = w_1 d_1^{+} + w_2 d_2^{-} + w_3 d_3^{-} \tag{5.43}$$

Where,

$$w = Weight\ expressing\ the\ relative\ improtance\ of\ achieving\ the\ goal$$

$$d^+, d^- = Deviational\ variables\ including\ over\ and\ under\ achievement\ of\ the\ goal$$

$Subject\ to$:

$$\left(\frac{Cost - Cost_{LB}}{Cost_{UB} - Cost_{LB}}\right) + (d_1^- - d_1^+) = \left(\frac{Cost_{Goal} - Cost_{LB}}{Cost_{UB} - Cost_{LB}}\right) \tag{5.44}$$

$$\left(\frac{Reliability - Reliability_{LB}}{Reliability_{UB} - Reliability_{LB}}\right) + (d_2^- - d_2^+) = \left(\frac{Reliability_{Goal} - Reliability_{LB}}{Reliability_{UB} - Reliability_{LB}}\right) \tag{5.45}$$

$$\left(\frac{Availability - Availability_{LB}}{Availability_{UB} - Availability_{LB}}\right) + (d_3^- - d_3^+) = \left(\frac{Availability_{Goal} - Availability_{LB}}{Availability_{UB} - Availability_{LB}}\right) \tag{5.46}$$

$$AS_{m1} = 0, \qquad \forall\ m = 1, \dots, M \tag{5.47}$$

$$AS_{mt} = (AE_{mt-1})Z_{mt} + (\alpha_m . AE_{mt-1}). X_{mt}, \quad \forall\ m = 1, \dots, M\ ;\ t = 2, \dots T \tag{5.48}$$

$$AE_{mt} = AS_{mt} + \frac{L}{T}, \qquad \forall\ m = 1, \dots, M\ ;\ t = 1, \dots T \tag{5.49}$$

$$X_{mt} + Y_{mt} + Z_{mt} = 1 \tag{5.50}$$

$$AS_{mt}, AE_{mt} \geq 0 \tag{5.51}$$

$$X_{mt}, Y_{mt}, Z_{mt} = \{0, 1\} \tag{5.52}$$

5.5 Data and Computational Results Summary

Gas absorption subsystem data is used to illustrate the effectiveness of the proposed optimization model as shown in Table 5.1 and 5.2. The data was collected and normalized based on the equipment condition and experience from field experts to represent a real plant situation. Seven equipment items and a 24 month planning horizon are considered in this problem.

Table 5.1: Maintenance Task Cost Data

Equipment (m)	CLF_m	CLR_m	CM_m	CLI_m	ρ_m
1	170	80	80	60	2
2	210	135	95	120	2.5
3	210	135	95	120	2.5
4	170	80	80	60	3
5	170	80	80	60	3
6	120	80	80	60	1.5
7	120	80	80	60	1.5

Table 5.2: Maintenance Task Duration and Reliability Data

	Durations of Tasks (Hours)				**Reliability Parameters**			
Equipment (m)	TF_m	TR_m	TM_m	TI_m	ERI	β_m	λ_m	α_m
1	24	6	4	0.3	6	1.6	2293	0.4
2	36	8	2	0.4	9	1.4	3434	0.6
3	40	8	2	0.4	8	1.5	6574	0.6
4	20	6	3	0.2	5	1.2	7598	0.5
5	16	6	3	0.2	4	1.3	9057	0.4
6	24	4	4	0.15	8	2.1	15065	0.3
7	24	4	4	0.15	6	1.9	13263	0.3

5.5.1 Gas Absorption System: Maintenance Cost, Reliability, and Availability

To illustrate the formulation effectiveness, a real gas absorption system of a gas plant is used [4]. Total maintenance cost with existing maintenance schedule is calculated and later compared with the optimized maintenance cost obtained using the proposed formulation. Generally, a plant consists of rotating equipment and static equipment, along with instrumentation and control devices. Static equipment usually has predefined inspection and maintenance schedules to ensure equipment integrity is in line with regulatory requirements; but rotating equipment has no fixed plan other than original equipment manufacturer (OEM) recommendations, so a great opportunity exists to optimize machinery maintenance. A real plant gas absorption subsystem, as shown in Figure 5.4, is considered to evaluate the proposed optimization formulation.

5.5.1.1 Total Maintenance Cost using the Current Maintenance Schedule

Existing maintenance model is based on time-based maintenance regardless of the condition of the equipment as the work orders are automatically generated by computerized maintenance management system. Sometimes, all the tasks within an operating unit occur together and cause scheduling problem of available resources. Using the existing maintenance model, the cost is calculated as shown in Table 5.3 and an existing maintenance schedule is shown in Table 5.4. Total maintenance cost, including both the maintenance and failure is around $ 33,092 over a period of 2 years. In this cost estimation, materials cost is not included because it varies among failures and, similarly, the materials cost is excluded while calculating the maintenance cost using the proposed formulation.

5.5.1.1.1 Estimation of Current Maintenance Cost

In this Section, the total existing maintenance cost and duration of the task are estimated. Mathematically, the function of the total maintenance cost is given below:

$$Total\ Cost\ (TC) = \sum_{m=1}^{7} \sum_{t=1}^{24} [CM_m + CR_m + CO_m] + [CF_m] \tag{5.53}$$

A processing plant usually consists of thousands of equipment items, and there is a great opportunity for optimizing maintenance costs, which is one of the reasons maintenance optimization is a highly demanded area in research and industry.

Table 5.3: Existing Maintenance Cost

	Total	Maintenance Event	Failure Event
Maintenance Cost – US$	33,092	29,592	3,500

Table 5.4: Existing Maintenance Schedule for Gas Absorption System

Planning Horizon (Month)																							
Equipment (m1 – m5)																							
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
		M			M			M			M			M			M			M			M
											R												R
Equipment (m6 – m7)																							
I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
		M			M			M			M			M			M			M			M
																							R

5.5.1.1.2 Estimation of Existing System Reliability and Availability

The overall system availability is estimated using the state dependent model. The model shown in Figure 5.4 is used and only related equipment is considered in this estimation. The general equation for n independent equipment items operating in a series has an equipment availability, $A_i(t)$; and the system availability is given by Equation 5.55:

$$A_s(t) = \prod_{i=1}^{n} A_i\,(t) \tag{5.54}$$

Where,

$$A_i\ = Avialability\ of\ system\ i$$

In general, availability of a system can be written as,

$$A_i = \sum_{\substack{all\ sucess \\ sates\ i}} P_i \tag{5.55}$$

Where,

$$P_i\ = Probability\ of\ system\ in\ success\ states$$

Similarly, the system reliability equation for a unit having series system can be written as,

$$R_S(t) = \prod_{i=1}^{n} R_i\,(t) \tag{5.56}$$

Where,

$$R_i = Reliability\ of\ equipment\ i$$

The reliability is also estimated using the simplified system as shown in Figure 5.4. To capture the uncertainty in the failure data, a 2.5% sensitivity factor is used. These values represent the existing availability ranging from 96.4-98.8%, whereas reliability ranges from 92.0-94.4%, as shown in Table 5.5.

Table 5.5: Gas Absorption System – Availability and Reliability

Description	**Values**
Availability	96.4 - 98.8%
Reliability	92.0 - 94.4%

The results obtained from the existing maintenance schedule are discussed and compared with the proposed formulation model results.

5.5.2 Proposed Formulation Model Results

In this Section, three developed models are solved. The proposed single objective optimization models and goal programming are solved using LINGO 14.0. It is a comprehensive platform designed to build and solve linear, nonlinear, stochastic, and integer optimization models. It includes a powerful language for expressing optimization models with built-in solver [36]. The outcome and results are discussed below.

5.5.2.1 Model 1 - Minimum Cost subject to Reliability Constraint

In this model, two cases at different target reliability are solved. The value of an objective function for the optimum solution at 90% reliability is $8,450.30 compared to the existing maintenance cost of $ 33,092. In the second run, the maintenance cost at a target reliability of 95% is $27,422 compared to the similar reliability and total cost of $33,092. Proposed models suggest a 17% improvement in maintenance cost when compared to similar reliability targets. A good mix of maintenance, inspection and replacement tasks are observed. It can be also be concluded that by increasing the reliability threshold the number and frequency of replacement actions increases. Tables 5.6 and 5.7 show the schedules of the optimized maintenance activities at given reliability targets.

Table 5.6: Total Maintenance Cost Subject to Reliability Constraints

Total Cost = $8450.3; Reliability = 90.0%

m	Planning Horizon (Month)																							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I	R	I	I	I	I	I	I	I
2	I	I	I	I	I	I	I	I	I	I	M	I	I	M	I	I	I	I	I	I	I	I	I	I
3	I	I	I	I	I	I	I	I	I	I	I	M	I	I	I	M	I	I	I	I	I	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
6	I	I	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I	R	I	R	I	I	I	I
7	I	I	I	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I	R	I	I	I	I	I

Table 5.7: Total Maintenance Cost Subject to Reliability Constraints

Total Cost = $ 27,422.1; Reliability = 95.0%

m	Planning Horizon (Month)																							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	R	R	M	R	M	R	R	R	R	R	R	I	R	M	R	R	R	R	R	R	R	R	R
2	I	I	I	M	M	M	M	M	M	I	I	R	I	M	M	M	M	M	M	M	M	M	I	I
3	I	I	I	M	M	M	I	I	R	I	I	M	M	M	M	M	M	M	M	M	M	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	R	I	I	I	I	I	I	R	I	I	I	I	I	I	I	I	R	I	I
6	I	I	R	I	R	I	R	I	R	I	R	I	I	R	I	I	R	I	I	I	I	I	R	I
7	I	I	I	R	I	R	I	R	I	R	I	R	I	R	I	R	I	I	I	I	I	R	I	I

The ERI can be effectively utilized in the scenarios where multiple tasks are required to be schedules, as in case of the schedule in Table 5.7. The use of the ERI in such cases makes it useful for field engineers and maintenance planners to plan maintenance on critical equipment prior to scheduling less critical equipment to avoid consequences posed by the failure of critical equipment. Table 5.8 shows the impact of equipment criticality on the maintenance schedule and this becomes very useful during the scheduling of a complete unit or plant maintenance tasks.

Table 5.8: Effect of ERI on the Maintenance Schedule

Total Cost = $ 27,422.1; Reliability = 95.0%

m	ERI	Planning Horizon (Month)																							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
2	**9**	I	I	I	M	M	M	M	M	M	I	I	R	I	M	M	M	M	M	M	M	M	M	I	I
3	**8**	I	I	I	M	M	M	I	I	R	I	I	M	M	M	M	M	M	M	M	M	M	I	I	I
6	**8**	I	I	R	I	R	I	R	I	R	I	R	I	I	R	I	I	R	I	I	I	I	I	R	I
1	**6**	I	R	R	M	R	M	R	R	R	R	R	R	I	R	M	R	R	R	R	R	R	R	R	R
7	**6**	I	I	I	R	I	R	I	R	I	R	I	R	I	R	I	R	I	I	I	I	I	R	I	I
4	**5**	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	**4**	I	I	I	I	I	R	I	I	I	I	I	I	R	I	I	I	I	I	I	I	I	R	I	I

5.5.2.2 Model 2 - Maximize Reliability subject to Availability Constraint

In this model, two cases at different target availability are solved. The value of the objective function, reliability, for the optimum solution at 80% availability is 90.2%. In the second run, the value of the objective function is 89.1% at a target availability of 85%. A mix of maintenance, inspection, and replacement tasks are observed. The results show that, with the increase in availability threshold, the system is performing more inspections compared to maintenance and replacement task as evident in the schedules.

Table 5.9 and Table 5.10 show the detailed schedules of the optimized maintenance activities at given availability targets.

Table 5.9: Maximize Reliability Subject to Availability Constraint

Reliability = 90.2%; Availability = 80.0%

m	Planning Horizon (Month)																						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I	R	I	I	I	R	I	I	I
2	I	I	I	I	I	I	I	I	I	I	I	M	I	I	I	I	I	I	I	I	I	I	I	I
3	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
6	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I	I	I
7	I	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I	I	I	I	R	I	I	I	I

Table 5.10: Maximize Reliability Subject to Availability Constraint

Reliability = 89.1%; Availability = 85.0%

m	Planning Horizon (Month)																						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	I	I	I	I	I	I	R	I	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I
2	I	M	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
3	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
6	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I
7	I	I	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I	I	I	R	I	I	I	I

5.5.2.3 Model 3 – Minimization of Deviation from Goals using Goal Programming

In this model, minimization of deviation, as an objective function, is developed using a goal programming approach. Deviations are minimized from the goal using an achievement function. All three criteria were used with different goals and weights to come up with strategies. Table 5.11 shows the different runs with assigned goals and weights. The goal programming model is flexible as different goals and weights can be assessed in a dynamic way and schedules can be adjusted on the plant requirements.

Table 5.11: Goals and Weights for Goal Programming

Exp.		**Total Maintenance Cost**	**Reliability**	**Availability**
E - 1	Goal	6000	1	1
	Weight	1	0	0
E - 2	Goal	6000	1	1
	Weight	0	1	0
E - 3	Goal	6000	1	1
	Weight	0	0	1
E - 4	Goal	6000	1	1
	Weight	0.5	0.4	0.1
E - 5	Goal	6000	1	1
	Weight	0.3	0.6	0.1

Table 5.12 and 5.13 shows the optimized maintenance schedule. Table 5.11 shows the results in the form of maintenance cost, reliability, and availability under predefined goal and weights. Many required scenarios can be run by changing the weights and goals. The maintenance cost of $7,589.5 is estimated with a reliability of 89.0% and availability of 86.4% subject to cost, reliability, and availability weights of 0.5, 0.4, and 0.1, respectively. The maintenance cost of $8,749.7 is estimated with a reliability of 90.3% and

availability of 80.3% subject to cost, reliability, and availability weights of 0.3, 0.6, and 0.1, respectively. Other scenarios can be developed and evaluated based on the business requirements to come up with optimized maintenance schedule. The goal programming model was solved using LINGO software to find out the optimal maintenance policy, and cost under different weights and goals.

Table 5.12: Schedule – Weights for Cost: 0.5, Reliability: 0.4, and Availability: 0.1

E4: Total Cost = $7,589.5; Reliability = 89.0%; Availability = 86.4%

m	Planning Horizon (Month)																						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I	I	R	I	I	I	I	I	I	I
2	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
3	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
6	I	I	I	I	I	R	I	I	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I
7	I	I	I	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I	I	I	I	I	I

Table 5.13: Schedule – Weights for Cost: 0.3, Reliability: 0.6 and Availability: 0.1

E5: Total Cost = $8,749.7; Reliability = 90.3%; Availability = 80.3%

m	Planning Horizon (Month)																						
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	I	I	I	I	I	I	I	R	I	I	I	R	I	I	I	I	R	I	I	I	I	I	I	I
2	I	I	I	I	I	I	I	I	I	I	M	I	I	M	I	I	I	I	I	I	I	I	I	I
3	I	I	I	I	I	I	I	I	I	M	I	I	I	M	I	I	I	I	I	I	I	I	I	I
4	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
5	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
6	I	I	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I	R	I	I	I	I	I
7	I	I	I	I	I	R	I	I	I	I	R	I	I	I	I	I	I	I	R	I	I	I	I	I

Table 5.14 summarizes the results of the goal programming model with certain model runs, goals, and weights can be changed to evaluate the other scenarios.

Table 5.14: Summary of Results – Goal Programming

	Total Maintenance Cost	Reliability	Availability
E - 1	5,645.9	0.810	0.977
E - 2	98,038.6	0.970	0.018
E - 3	5,645.9	0.810	0.977
E - 4	7,589.5	0.890	0.864
E - 5	8,749.7	0.903	0.803

5.6 Conclusion

This research work proposes two nonlinear mixed-integer optimization models and a goal programming model for maintenance scheduling of a complex real plant gas absorption system of a hydrocarbon facility. These proposed formulation attempts to minimize cost and maximize reliability, and the goal programing model handles multiple and conflicting objective to optimize the maintenance schedule. The proposed models have given promising results and proved to be a useful tool to industry for handling maintenance scheduling optimization under various constraints. The proposed model successfully optimized the existing maintenance schedule of a gas absorption system and suggested 17% improvement in maintenance cost when compared to similar system reliability levels. A huge maintenance cost improvement is expected, once the proposed model is applied to a complete plant. The goal programming model provides flexibility to engineers and planners to develop maintenance schedules considering different conflicting objectives. The overall results derived from the proposed optimization models confirm the applicability of the approach to real-world maintenance optimization problem and its application to other asset intensive industries where maintenance is important to ensure safety, availability, and reliability of the facilities.

In future work, the proposed formulation will be extended to solve similar problems and compare the effectiveness of the results using multi-objective meta- heuristic techniques.

CHAPTER 6

CONCLUSION, CONTRIBUTIONS AND FUTURE WORK

6.1 Introduction

Availability is an important measure in complex systems and applicable to many industries, such as refineries, gas plants, power systems, and communication. It is a key measure to have confidence in the processes used to meet requirements for meeting production, safety, and financial targets. Availability and reliability are considered, but both are different. High reliability on its own is not sufficient to ensure system availability. Quick restoration of equipment back to service, essentially termed as maintainability, is also important for maximization of availability. Different industries have different requirements for availability to meet customer expectations. There are many ways to maximize availability such as optimized and robust design, cost, manpower, skill level of the maintenance crew, etc. In the communication and power sector, high availability is obtained through redundant, highly reliable equipment, and schedule maintenance [1]. Power systems are designed for availability close to 100%, using modest reliable design but highly redundant and perfectly maintained equipment with a sharing option. In the process industry, availability is achieved by highly reliable equipment with low maintainability [1]. The significance of availability in different industries makes it an important topic for research. The need for availability improvement has motivated authors to contribute by developing some new and novel methods to address this most desired area of industry interest.

In this research, availability estimation and management is addressed by focusing on different areas such as risk-based availability estimation; early fault detection; effective equipment failure investigation; and maintenance scheduling optimization. Based on the author’s experience, developments in these areas can significantly contribute to addressing availability.

6.2 Research Contributions

In this thesis, an overall solution is developed to estimate and manage the availability of complex processing systems and plants. Availability is an important factor for companies to use to reap real benefits from monitoring and managing equipment. The benefits of managing availability have many facets, such as high reliability, low maintainability, optimized plant design, and cost. The need for availability estimation and management models provides us an opportunity to work on this topic and develop tools and models that can be used effectively to benefit different organizations and to help them achieve their objectives. As discussed earlier, availability is a key performance parameter, which is applicable to many industries. Availability management is a process, if managed correctly, can be used to optimize design, cost, safety, reliability, availability and maintainability.

Following is a summary of the major contributions of this dissertation.

- ***Availability Estimation using Markov Process***

  An overall risk based availability estimation process using Markov is developed. In general, asset intensive industries, such as refineries and petrochemical plants, have thousands of equipment items, which make it difficult to estimate equipment and system availability. This research addresses the concern by developing a risk-based availability estimation methodology using state-dependent models. It includes an introduction to Markov modeling, and its usefulness and limitations. State models and other modeling work are performed. The developed model successfully validated using the gas absorption unit.

- ***A Framework to Address Failure to Enhance Safety and Availability***

  A novel risk-based failure assessment approach to address safety and availability of the complex operating systems is developed. There are many different failure assessment processes; however, they are more focused on failure investigation rather addressing the issue holistically. In this work, we have contributed by developing a structured process to encompass all the action needed perform assessment to enhance availability and safety. Later, the concept is validated using the real-world failure assessment cases to prove the applicability and efficacy of the proposed model.

- ***Fault Detection to Improve Availability using Decision Trees***

  As discussed earlier, availability encompasses maintainability and reliability. The novel idea in this work was to develop algorithm using machinery data to detect early faults prior they became threat to unscheduled downtime. Early fault detection indeed helps improving reliability and availability, hence, ensure availability. To detect early faults, a novel fault detection and management model is developed using decision trees to support system availability and safety improvement. Decision trees model is developed in MATLAB as a predictive data mining tool to detect early faults, and their management to improve system availability. To conclude the effectiveness of the model, the proposed model was successfully tested to detect faults using real plant machinery vibration data.

- ***Multi-Constrained Maintenance Scheduling Optimization***

  Maintenance is vital for improving the availability and reliability of the equipment and facilities. Multi-constrained, multi-objective maintenance scheduling optimization models are proposed using exact and optimized solutions. The model was developed in commercial software LINGO to solve optimization problem. The optimization problem was developed considering the time-dependent equipment failure rate to optimize maintenance cost at different availability and reliability levels. Different optimization scenarios were considered, such as minimization of cost, maximization of availability and reliability etc… These models were applied on a plant scenario to show the effectiveness of maintenance scheduling optimization on cost, availability, and reliability.

- ***Physical Asset Management***

  An introduction of physical asset management is carried out to understand the difference between maintenance management and performance management. This area is of great interest now a days and latest development in this field is issuance of ISO 55000 series guidelines for asset management. Maintenance and performance management are both necessary for improving system availability. We also explored the assumptions and limitations to efficient asset management. This research also attempted to answer why PAM is important and also emphasized its relationship to cost, maintenance, and availability management. In order to validate its effectiveness, the asset management concept was applied to real plant and great results have realized.

6.3 Conclusion

In this dissertation, new models, approaches and algorithms have been explored to estimate and manage the availability of complex hydrocarbon processing systems. The risk of equipment failure and its effect on availability is vital in the hydrocarbon industry, and is also explored in this research. The importance of availability is encouraging companies to invest in this domain by putting efforts and resources in developing solutions for enhancing system availability. This research works toward developing an integrated and systematic strategic framework to achieve system availability targets. The main focus areas in this research are to address availability estimation and management through physical asset management, risk-based availability estimation strategies, availability and safety using a failure assessment framework, and availability enhancement using early equipment fault detection and maintenance scheduling optimization.

In conclusion, this research will contribute to the field by providing a wide range of solutions to industry in terms of availability estimation and management. The challenges faced during the research, such as the availability and quality of the equipment historical data, is dealt by normalizing the data with experience and recommendations from subject matter experts. The algorithms, models, and solutions developed and presented in this dissertation are valuable for estimating system availability and management. The proposed solutions can assist strategic and tactile plant management in making decisions; and to effectively and efficiently optimize system availability and cost.

6.4 Recommendations for Future Research Work

In this research, along with development of new methods, we have key findings to enhance or extend the developed work. Some of them are discuss below:

1. A risk-based methodology of availability estimation is proposed. This methodology assumed a constant failure rate, but work can be extended to develop state-dependent models with different failure behaviors. The model can be extended to equipment dominant failure modes. The flexibility of state-dependent models can be very

useful in these circumstances. Not only in regard to failure mode but also for other constraints such as maintenance manpower, delays related to obtaining spare parts, and equipment release for maintenance can be included to extend this work.

2. A risk-based failure assessment framework is explored for managing availability and safety. This work can be extended to develop software tools which provide users with a graphic user interface to follow the proposed framework. The proposed framework has four key phases, which require multiple data handling and storage solutions. A software tool developed based on the proposed framework greatly helps with streamlining the process. It will also help with storing evidence, photos, and other documents in a common database. Along with these benefits it will help with the tracking and implementation of the recommendations.

3. Fault detection is an important aspect of availability enhancement. A decision tree-based fault detection scheme is proposed in this dissertation, but there are other algorithms available to detect incipient machinery faults. The work can be extended to evaluate the performance of other algorithms and filtering techniques in detecting machinery faults such as neural networks, Kalman filters, real coded genetic algorithms, wavelet-based algorithms, and other hybrid algorithms. The suggested work extension will explore the efficiency and suitability of decision trees and other algorithm responses to detect incipient faults. The work can also be extended to explore other machinery failure modes such as cracked shafts, rubbing, looseness, etc.

4. Maintenance optimization is an area of research for ensuring the safety, reliability, and availability of equipment and systems. The exact and Pareto-optimal

solutions for multi-constrained maintenance scheduling optimization are discussed in this dissertation. This work can be extended to optimize maintenance scheduling to include other constraints such as maintenance manpower, equipment shutdown opportunity, seasonal product demand changes, and spare availability. There are optimization algorithms such as harmony, nature-inspired optimization, simulated annealing, and other hybrid algorithms that can be explored further to develop maintenance schedules and compare their optimization efficiency with proposed genetic algorithms.

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