

Model-based fault diagnosis framework for effective predictive maintenance

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Preface

This dissertation focuses on eliminating the incessant outage of equipment in Nigerian manufacturing industry through application of model based fault diagnosis technology.

In examining the issue of endemic equipment downtime in the Nigerian manufacturing industry, the study employed the use of case studies, published journals on predictive maintenance and model based fault diagnosis, relevant literature, interviews, observation technique, internet resources, and experimental prototype.

I would like to express my sincere gratitude to my supervisor, Professor Harry Wichers, from the Faculty of Engineering Centre for Research and Continued Engineering Development (CRCED) for his support, guidance and unreserved attention that have led to the successful completion of this dissertation.

I am also grateful for the support, resources, and information given to me by the management and staff of some Nigerian manufacturing companies used as case studies.

Finally, I lift my praise to God almighty, for His unending Grace and ever-present Favour that have seen me through, from beginning to the end of this study. Indeed, He is the alpha and omega of my life.

Babatunde Akindele

*To my pretty wife and my loving parents,
whose love, fortitude will be a fountain of joy and inspiration forever.*

Abstract

Predictive maintenance is a proactive maintenance strategy that is aimed at preventing the unexpected failure of equipment through condition monitoring of the health and performance of the equipment.

Incessant equipment outage resulting in low availability of production facilities is a major issue in the Nigerian manufacturing environment. Improving equipment availability in Nigeria industry through institution of a full featured predictive maintenance has been suggested by many authors. The key to instituting a full-featured predictive maintenance is condition monitoring.

Primarily, this research is focused on how to reduce the prevalent of equipment downtime in the Nigerian manufacturing industry, through the application of Model Based Fault Diagnosis technology as a condition monitoring tool for enhancing predictive maintenance practices in Nigerian manufacturing industry.

The following objectives underscore the aim of this research work:

- To assess the implementation and performance of predictive maintenance practices in some selected manufacturing companies in Nigeria and verify if there is need for improvement in these practices.
- To identify the challenges and barriers to the implementation and performance of full-featured predictive maintenance practice in the Nigerian manufacturing industry.
- To develop a framework for enhancing quality of Predictive Maintenance practices in the manufacturing industry in Nigeria through a Model Based Fault Diagnosis and Decision Support System.

- To validate that the developed framework meets the Nigerian manufacturing industry needs through the implementation of a prototype in one of the selected manufacturing companies in the case study.

The empirical investigation undertaken as part of this research revolves around five (5) of the Nigerian manufacturing companies. Personal interviews were also adopted as means of data collection.

The research outcomes reveal the followings:

- Top management commitment to the implementation of predictive maintenance strategies in the Nigerian manufacturing industry is inadequate.
- Many of the manufacturing companies lack a tool for carrying out continuous condition monitoring in their predictive maintenance program. This is responsible for poor performance of most predictive maintenance programs in Nigerian manufacturing industry.
- Inadequate training on the implementation of predictive maintenance principles is adversely affecting the proficiency of personnel in adopting philosophy that underlies practices of predictive maintenance.
- The size of equipment part inventory, maintenance work backlog and machine scraps are also enormous in the maintenance yards of the companies.
- Nevertheless, the implementation of predictive maintenance program has a positive impact on the equipment availability of one of the case studies. Management commitment in Chemical and Allied Products (CAP) Plc is outstanding. Application of intelligent condition monitoring system, and personnel training and competence are vital to the success of Predictive Maintenance implementation in CAP Plc.

The specific deliverable from this research is a proposed framework (**MBFDF**) for effective implementation of predictive maintenance strategy through application of model based fault diagnosis technology, which can be adopted to improve performance of predictive maintenance practices in the Nigerian manufacturing industry.

The deliverable also includes a soft copy of data in Excel spreadsheet obtained during experimental test of the proposed framework in a small manufacturing company in Nigeria.

In this research, a model based fault diagnosis framework (**MBFDF**) to serve as a condition monitoring and decision support tool for predictive maintenance programs in Nigerian manufacturing industry was developed. Implementation to verify the real-life implementability and effectiveness of the proposed framework was performed in one of the companies used for the case study.

A comparison of results with pre-integration predictive maintenance program is presented, showing the implementability and the effectiveness of the proposed MBFDF for condition monitoring in predictive maintenance programs in the Nigerian manufacturing company.

Recommendations presented in this dissertation are also vital to the success of implementing predictive maintenance program in Nigerian manufacturing companies.

Table of contents	Pages
Preface	ii
Abstract	iv
Table of Contents	vii
List of Figures	xi
List of Tables	xii
List of Acronyms and Abbreviations	xiii
Definitions of Keywords	xiv
1.0 Introduction.....	1
1.1 Motivation	2
1.2 Problem Statement	2
1.3 Research Aim and Objectives.....	5
1.4 Outputs and Deliverables.....	6
1.5 Scope of Research Work	7
1.6 Research Outline	7
1.7 Research Contributions.....	8
2.0 Literature Review.....	10
2.1 Maintenance: Introduction and History.....	11
2.1.1 Maintenance Roles in an Organization.....	12
2.1.2 Maintenance Strategy in Industry.....	14
2.2 Predictive Maintenance Approach	16
2.2.1 Techniques	18
2.2.2 Benefits and Prospects.....	21
2.2.3 Extending Predictive Maintenance Program Scope.....	23

Table of contents (continued)

2.2.4	<i>Evidence of Industrial Application of Predictive Maintenance.....</i>	24
2.2.5	<i>Predictive Maintenance Systems.....</i>	28
2.3	Fault Diagnosis: Introduction.....	32
2.3.1	<i>Traditional Fault Diagnostic Approaches.....</i>	34
2.3.2	<i>Model Based Fault Diagnosis</i>	36
2.3.3	<i>Industrial Application of Model Based Fault Diagnosis</i>	39
2.4	Maintenance Practises in Nigerian Manufacturing Industry.....	46
2.4.1	<i>Challenges of the Nigerian Manufacturing Industry.....</i>	47
2.5	Summary	48
3.0	Empirical Investigation.....	49
3.1	Research Overview.....	50
3.2	Research Approach	50
3.3	Primary Data Collection Method	52
3.3.1	<i>Case studies.....</i>	52
3.3.2	<i>Selecting the Pilot plant.....</i>	53
3.3.3	<i>Personal Interview.....</i>	54
3.4	Existing implementation of Predictive Maintenance in the manufacturing Industry.....	55
3.4.1	<i>Management and Work Culture.....</i>	55
3.4.2	<i>Maintenance Processes.....</i>	56
3.4.3	<i>People Skills/ Human resources.....</i>	56
3.4.4	<i>Technologies.....</i>	57
3.5	Secondary Data.....	57

Table of contents (continued)

3.6	Recommendations for Improving Predictive Maintenance Practices in the Manufacturing Companies in Nigeria	57
3.7	Summary	61
4.0	Results and Findings.....	62
4.1	Case Studies.....	63
4.1.1	<i>Case Study A: Mouka Limited.....</i>	<i>63</i>
4.1.2	<i>Case Study B: Nigerite Limited.....</i>	<i>65</i>
4.1.3	<i>Case Study C: CAP Plc Limited.....</i>	<i>67</i>
4.1.4	<i>Case Study D: Rommy Poly-products Limited.....</i>	<i>68</i>
4.1.5	<i>Case Study E: Poly-products Nigeria Limited.....</i>	<i>70</i>
4.2	Comparison of case studies.....	71
4.3	Correlation of Research Outcomes	74
4.4	Implementation of a prototype system.....	76
4.4.1	<i>Prototype Performance Assessment.....</i>	<i>78</i>
4.5	Summary.....	80
5.0	Discussion and Interpretation.....	82
5.1	Analysis of Observations and Interviews.....	83
5.1.1	<i>Predictive Maintenance Implementation: Management Approach.....</i>	<i>83</i>
5.1.2	<i>Predictive Maintenance Implementation: Application of Technology.</i>	<i>84</i>
5.1.3	<i>Predictive Maintenance Implementation: Maintenance Process.....</i>	<i>86</i>
5.1.4	<i>Predictive Maintenance Implementation: Human Resources.....</i>	<i>86</i>
5.2	Analysis of Prototype Implementation.....	87
5.3	Reducing Equipment Breakdowns.....	88

Table of contents (continued)

5.3.1	<i>The Model Based Fault Diagnosis Framework.....</i>	88
5.4	Summary.....	97
6.0	Recommendations and Conclusions	98
6.1	Conclusions.....	99
6.2	Recommendations for implementation of the proposed Model Based Fault Diagnosis Framework for effective predictive maintenance.....	100
6.3	Recommendations for further research.....	101
6.4	Limitations of the Study.....	102
	<i>Bibliography.....</i>	<i>104</i>
	<i>Annexure.....</i>	<i>123</i>
	<i>Annexure A: Prototype Application.....</i>	<i>124</i>
	<i>Annexure B: Prototype System Model.....</i>	<i>130</i>

Table of contents (continued)

List of Figures

<i>Figure 2.1 – Evolution of Maintenance Strategy (DOD CBM+ Guidebook).....</i>	<i>12</i>
<i>Figure 2.2 – Input-Output Model of Maintenance</i>	<i>14</i>
<i>Figure 2.3 – Advanced Maintenance Strategy Implementation.....</i>	<i>26</i>
<i>Figure 2.4 – PdM Implementation Return On Investment.....</i>	<i>26</i>
<i>Figure 2.5 – PdM Implementation Process Improvement Returns.....</i>	<i>27</i>
<i>Figure 2.6 – Process model of Predictive maintenance System.....</i>	<i>29</i>
<i>Figure 2.7 – Optimized Predictive Maintenance process chain.....</i>	<i>31</i>
<i>Figure 2.8 – Schematic description of the model-based fault diagnosis scheme.....</i>	<i>39</i>
<i>Figure 4.1 – Predictive Maintenance Implementation in CAP Plc Limited.....</i>	<i>75</i>
<i>Figure 4.2 – Model Based Diagnosis Reasoning.....</i>	<i>78</i>
<i>Figure 5.1 – Architecture of the proposed MBFDF framework.....</i>	<i>90</i>
<i>Figure A – Algorithm for the Model Based Diagnostic Engine.....</i>	<i>129</i>
<i>Figure B – Input –Output Model of the Compressor System.....</i>	<i>132</i>

Table of contents (continued)

List of Tables

<i>Table 4.1 – Comparison of case studies.....</i>	<i>71</i>
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Table of contents (continued)

List of Acronyms and Abbreviations

PdM	-Predictive Maintenance
CM	-Condition Monitoring
MBFDF	-Model Based Fault Diagnosis Framework
MTTF	- Mean Time To Failure
MTBF	- Mean Time Between Failure
DoD	-Department of Defence, US Army
CBM+	-Condition Based Monitoring
VMBD	-Vehicle Model-based Diagnosis
EU	- European Union
INDIA	- Intelligent Diagnosis in Industrial Applications
CFG	- Configuration Flow Diagram
CAP	- Chemical and Allied Products

Table of contents (continued)

Definitions of Keywords

Availability is defined as a percentage measure of the degree to which machinery and equipment is in an operable and committable state at the point in time when it is needed.

Condition Monitoring is a form of predictive maintenance used to monitor the conditions of a system in order to detect early warning of potential problems and virtually eliminate the need for periodic disassembly and inspection, and the possibility of an unexpected breakdown.

Diagnosis of a system is the task of identifying faulty components that cause the system to not function **as** it was intended.

Downtime or **outage duration** refers to a period of time that a system fails to provide or perform its primary function.

Fault is an unpermitted deviation of at least one characteristic property or parameter of the system from acceptable, usual, or standard conditions.

Fault Diagnosis is the task of determining the kind, size, location and time of a fault. It follows fault detection, and includes fault isolation and identification.

Model-based diagnosis is a technique that employs knowledge of how devices work and their connectivity in form of models.

Predictive maintenance is a proactive maintenance strategy that involves systematic continuous monitoring and trending of condition of a critical equipment to determine the condition of the equipment subject to degradation.

Residual is the measure of the deviation of plant outputs from the nominal model-based computations of the plant outputs.

1.0 Introduction

Chapter 1 introduces the dissertation research objective, stating the problem and stating the reasons why it is being researched.

1.0 INTRODUCTION

1.1 *Motivation*

Equipment failure is perhaps one of the major factors reducing availability of production plants. Reduction in availability of equipment can have amplified effects on the productivity of a production plant. Today, availability of plants must be optimal in order to lower production cost, meet safe operation requirements, and comply with increasing stringent environmental regulations. Furthermore, with the present manufacturing environment of imminent budget cuts and corporate downsizing, industries are searching for strategies to help maintenance and operation personnel to identify and correct system equipment problems before failure occurs.

Hence, effective predictive maintenance programs may be the essential key to prevent eventual failure or breakdown of equipment.

1.2 *Problem Statement*

Excessive downtime remains a problem for many organisations, particularly those using complex capital-intensive manufacturing processes (Davies and Greenough, 2008).

According to Ogaji and Probert (2006:2), equipment downtime seriously bedevils the productive capability of Nigerian industries, by reducing average rate of output, and increasing operating costs.

Effective maintenance ensures that the equipment is capable of doing what it was designed to do, when required. In Nigerian industries, maintenance is not given a

high priority and hence plants are often underutilized and run at high costs (Ogaji S., Probert S., 2006).

Many industries in Nigeria operate productively for less than 50 percent of even the nominally functioning hours per year. Nominally functioning hours per year are the expected total number of hours in a year a given industry or equipment is expected to function as intended. Part of this embarrassment is caused by high downtime and low spare-capacity to cope with sudden high demands (Ogaji S., Probert S., 2004).

These challenges are difficult to overcome in Nigeria. Nevertheless, maintenance is often the major activity to preserve the functionality of plants, accounting for up to 40% of total costs, in some Nigeria companies (Eti M., Ogaji S., Probert S., 2006).

Furthermore, several studies in a wide range of Nigerian industries indicate that indigenous low availability and low productivity of production equipment are endemic. The resulting closure of some of these manufacturing industries in Nigeria have triggered a realisation of the strategic challenges in maintenance management in the Nigerian manufacturing industry (Eti M., Ogaji S., Probert S., 2005).

In most companies in Nigeria, repair and replacement only ensue after a breakdown. Also failure data are rarely available. In the traditional general management of companies, maintenance is regarded as an expense that can easily be reduced in relation to overall business costs, particularly in the short term. This is a misguided opinion (Eti M., Ogaji S., Probert S., 2006).

With system availability becoming critical, issues such as reducing operating costs as well as the strategic importance of employing better and, if feasible, optimal maintenance schedules need to be more universally recognised and implemented (Eti M., Ogaji S., Probert S., 2004).

Furthermore, to increase the availability and reliability of equipment, more commitment is needed to maintenance. It is now increasingly realised that achieving better equipment availability and reliability requires prevention of equipment failures at the source rather than the more traditional approach of either letting the equipment fail before repairing it or “fire fighting” in the case of an emergency (Eti M., Ogaji S., Probert S., 2006).

Predictive maintenance (PdM) is a proven failure avoidance maintenance practice that is widely used in many industries. Typically, plants that have developed effective predictive maintenance programs using Condition Based Monitoring discover that monitored assets rarely cause unplanned problems or downtime (Philip Mosher, 2006).

Predictive maintenance is emerging in other industries as a compelling value. The automotive industry, for example, has been investing with proven value results for several years and their maintenance strategy has now matured beyond the development phase (Steve Fulton, Myungkill Kim, 2007).

In addition, the recession has encouraged the use of predictive maintenance tools. These tools are becoming more popular as plants struggle to extend the life of their equipment and optimize equipment operation in the midst of a severe downturn.

Plants can no longer afford scheduled maintenance—which often means replacing something that's not broken—or the costly fix-it-when-it-breaks maintenance strategies (Rob Spiegel, 2009).

The identified issues of excessive downtime in Nigerian manufacturing industries are adversely affecting productivity of many manufacturing companies in Nigeria. Hence, **urgent attention is needed to proffer a solution to the incessant downtimes in manufacturing companies in Nigeria.** Many authors suggested that instituting a full-featured predictive maintenance program incorporating process parameters may help to minimize equipment failure.

However, Yam, Tse and Tu (2001) reasoned that high maintenance costs in industrial firms highlight the need to enhance modern maintenance practices, and to use intelligent computer-based maintenance systems.

1.3 *Research Aim and Objectives*

The major thrust of this research is to appraise predictive maintenance implementation in five selected manufacturing companies in Nigeria with focus on identifying challenges and barriers to effective implementation of the maintenance practice in the companies. The findings will be used to develop a suitable framework, which if deployed, can improve quality of predictive maintenance implementations in the manufacturing industry in Nigeria.

The framework will seek to supplement the performance of conventional Predictive Maintenance approaches with the capability of an intelligent Model-base Fault Diagnosis and Decision Support System (FDDSS). This optimised Predictive

Maintenance framework will tend to improve quality and effectiveness of Predictive Maintenance in manufacturing industries in Nigeria.

Hence, the research work will involve case studies of five selected manufacturing companies with predictive maintenance implementation in Nigeria. The specific objectives include:

- To assess the implementation and performance of predictive maintenance practices in the selected manufacturing companies in Nigeria and verify if there is need for improvement in these practices.
- To identify the challenges and barriers to the implementation and performance of effective predictive maintenance practice in the Nigerian manufacturing industry.
- To develop a framework for enhancing quality of Predictive Maintenance practices in the manufacturing industry in Nigeria through a model based Fault Diagnosis and Decision Support System.
- To validate that the developed framework thereof meets the Nigerian manufacturing industry needs through the development of a prototype in a small manufacturing company in Nigeria.

1.4 Outputs and Deliverables

The specific deliverable from this research will be a developed and validated framework for an effective predictive maintenance program, which can easily be modified and implemented by manufacturing companies in Nigeria to improve the performance of their predictive maintenance practices.

The deliverable will include a soft copy of data in Excel spreadsheet obtained during experimental test of the proposed framework in a small manufacturing company in Nigeria.

1.5 *Scope of Research Work*

The focus of the research and the subsequent development work is to provide the Nigerian manufacturing industry with a framework for the effective practise of predictive maintenance to improve their equipment availability.

The challenges that are normally faced with the implementation of Predictive Maintenance programs in the Nigerian manufacturing environment will be investigated by obtaining information through questionnaires and personal interviews.

Analysis of the collected information, through deduction, will be used to identify '*focus areas*' in the existing implementations of predictive maintenance as compared to 'best practices' predictive maintenance programs in a world class organization.

The identified '*focus areas*' in conjunction with information from relevant literature review will be used to develop the improved framework for an effective Predictive Maintenance implementation program for manufacturing companies in Nigeria.

1.6 *Research Outline*

This dissertation work is outlined in six chapters. Chapter two of this dissertation contains a relevant literature review of existing work on the application of fault diagnosis technologies to optimize the implementation of predictive maintenance practices in the industry.

Chapter three documents the research design and methodology followed, and gives insight on the primary data collection methods and procedures used in carrying out the research work.

The fourth chapter presents the results and findings of the survey done at some specific manufacturing plants in Nigeria.

Chapter five analyses the results and findings of the research and thereby develop a framework for the implementation of an effective Predictive Maintenance System. Furthermore, the developed framework and current implementation of a predictive Maintenance practice in one of the selected companies is compared through sampling of managers, supervisors and employees opinion of the new framework.

An overall outcome of the research, recommendations and conclusion, is presented in chapter six.

1.7 *Research Contributions*

Overall, the research is intended to provide the following contributions:

- To broaden the knowledge of maintenance managers in Nigeria on the implementation of predictive maintenance practices.
- To improve the Overall Equipment Effectiveness (OEE) through optimization of predictive maintenance programs in the manufacturing industry in Nigeria.
- To assist both operations and maintenance personnel in prompt diagnosis of equipment faults as well as to reduce maintenance downtime and cost.
- To improve the utilization of Operation Routine Data (ORD) for equipment fault diagnosis and decision-making for maintenance planning and schedule.

- To establish a simple and non-complex computer based approach to effective predictive maintenance in general and to execute fault diagnosis through the application of an inexpensive but effective model based fault diagnosis system.

2. Literature Review

Chapter 2 contains information on maintenance practises and relevant literature, which aid to explain the implementation benefits of adopting Optimized Predictive Maintenance programs in the manufacturing industry in Nigeria. .

2.0 LITERATURE REVIEW

2.1 Maintenance: Introduction and History

Maintenance is undertaken to preserve the proper functioning of a physical system, so that it will continue to do what it was designed to do (Eti M., Ogaji S., Probert S., 2004). Many authors traced the practice of maintenance to ancient civilization when the development of effective irrigation agriculture to meet food demands and contain famines became necessary (<http://historyworld.org/civilization>).

Maintenance practises gradually evolved and became more popular as the complexity in industry systems increased. Asgarpoor and Doghman (1999) explained that during the Pre-World War II era, industry was not very highly mechanised because the equipment used were very simple which made them easy to fix. Hence companies performed mainly *Corrective Maintenance (CM)*.

However, during the Post-World War II until the mid 1970's era, increased mechanization led to more numerous and complex equipment. Companies were beginning to rely heavily on this equipment. This dependence led to the concept of *Preventive Maintenance (PM)*.

Moreover, in the latest era of maintenance beginning in the mid 1970's, the huge costs of new highly-mechanized equipment resulted in companies wanting to ensure that equipment lasted and operated correctly for as long as possible. This era also marked an increased awareness in safety and environmental consequences. Accordingly, failures usually attract attention because they can adversely affect output, safety, environmental health, quality of end product, customer service, competitiveness and unit costs (Eti M., Ogaji S., Probert S., 2004). Thus, the impact

of downtime became significant leading to introduction of maintenance approaches like Proactive Maintenance, Reliability Centred Maintenance (RCM), Total Productive Maintenance (TPM) etc.

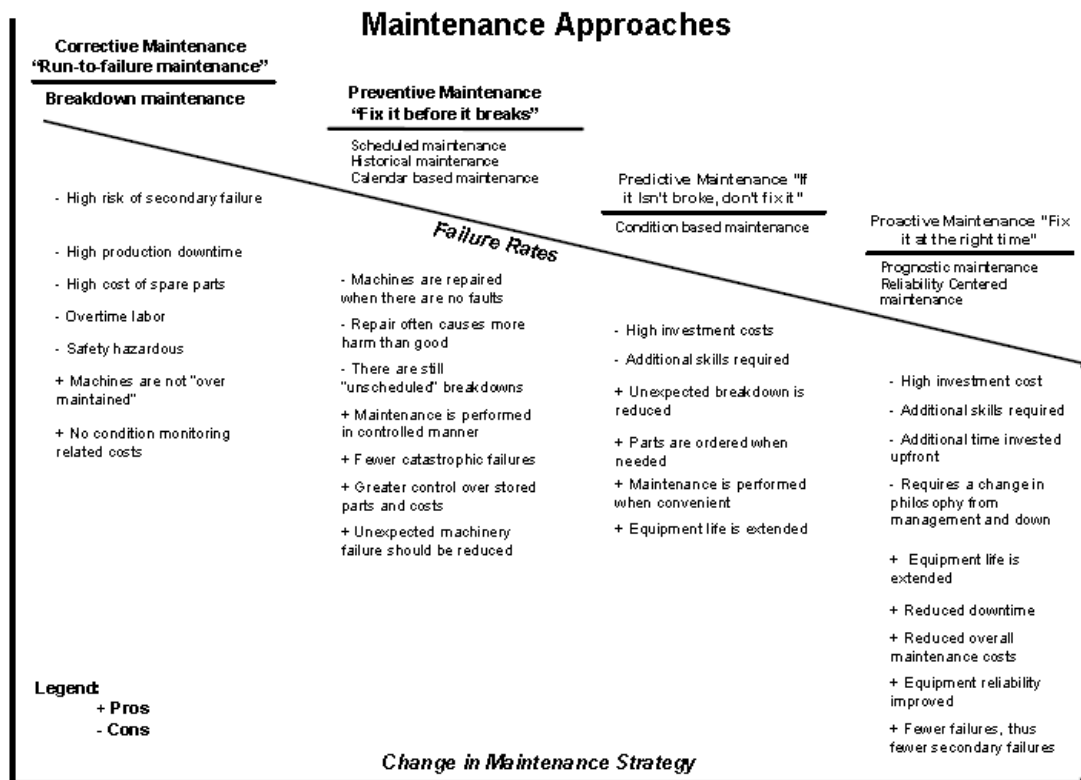


Figure 2.1 Evolution of Maintenance Strategy (DOD CBM⁺ Guidebook)

2.1.1 Maintenance Roles in an Organization

A huge opportunity for improving manufacturing productivity is in plant maintenance (Franklin Scott, 1994). Eti M., Ogaji S., Probert S., (2004) noted that maintenance affects business profitability. However, until recently, maintenance has not always been considered a main-stream function. It has always been seen as a negligible sub-system of production and probably, a necessary and an unplanned overhead.

Contrary to popular opinion, the role of maintenance is not to “fix” breakdown in record time; rather, it is to prevent all losses that are caused by equipment or system related problems (Mobley, 2002). The author went further to say that the normal practice of quick response to failures must be replaced with maintenance practices that sustain optimum operating condition of all plant systems. He concluded that failure prevention, not quick-fixes of breakdown, should be the objective of maintenance programs.

Many authors have suggested that for an effective maintenance programs, the primary roles of maintenance should include:

- Optimum plant availability.
- Optimum plant operating conditions.
- Maximum utilization of maintenance resources.
- Optimum equipment life.
- Minimum spares inventory.
- Ability to react quickly.

Visser (1998) modelled maintenance as a transformation process contained in an enterprise system as shown in *figure 2.2*. The model revealed that the way maintenance is performed in an organization will have effects on the availability of production facilities, the rate of production, quality of end product and cost of production, as well as the safety of the operation. These factors in turn will determine the profitability of the enterprise.

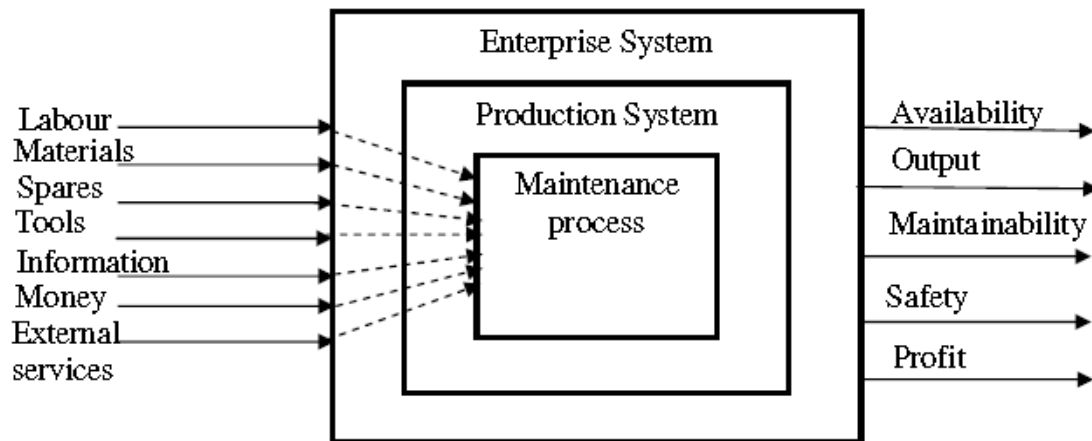


Figure 2.2 Input-Output Model of Maintenance

2.1.2 Maintenance Strategy in Industry

Nowadays maintenance is considered as a key point for the manufacturing system competitiveness because first its cost represents the major part of the operational cost, and second, a system failure can have an important impact on product quality, equipment availability, environment, and operator (Leger J, Neunreuther E, lung B and Morel G, 1998).

Mobley (2002), Asgarpour and Doghman (1999) and DOD CBM+ guidebook (2008) explained that most industrial and process plants typically employ two types of maintenance management: Reactive or Proactive maintenance.

Reactive maintenance (also called corrective maintenance or Run-to-Failure) waits for machine or equipment failure before any maintenance action is taken. According to DOD CBM+ Guidebook (2008), Reactive Maintenance is performed for items that are selected to run to failure or those that fail in an unplanned or unscheduled manner.

Reactive maintenance of a reparable item is almost always unscheduled in the sense the failure occurred unpredictably. Reactive maintenance restores an item to a serviceable condition after the failure has occurred.

Even though a plant using reactive maintenance may not spend any money on maintenance until a machine or system fails to operate yet reactive maintenance is perhaps the most expensive method of maintenance management.

According to Mobley (2002), analysis of maintenance costs indicates that a repair performed in the reactive or run-to-failure mode will average about three times higher than the same repair made within a proactive mode. Furthermore, other major expenses associated with run-to-failure maintenance practices are high spare parts inventory cost, high overtime labour costs, high machine downtime, and low production availability.

In contrast, *proactive maintenance* is carried to prevent a failure. In this context, proactive maintenance is considered either *preventive or predictive* in nature, and the maintenance performed can range from an inspection, test, or servicing to an overhaul or complete replacement.

The difference between these two types of proactive maintenance is related to the intervention strategy (Leger J, Neunreuther E, lung B and Morel G, 1998).

Preventive maintenance may be either scheduled or unscheduled; that is, it is initiated based on predetermined intervals or, alternatively, triggered after detection

of a condition that may lead to failure or degradation of functionality of an equipment, or component.

Basically, the strategy of the preventive maintenance is realised through a planning based on *Mean Time To Failure (MTTF)* and *Mean Time Between Failure (MTBF)*.

However, preventive maintenance generates over-cost when the device is replaced while its real life time is not reached, or it generates unavailability of the manufacturing system when the device failed before the theoretical life delay (Leger J, Neunreuther E, lung B and Morel G, 1998).

One solution to decrease the operational cost and to increase the manufacturing system availability is to manage continuously all maintenance activities and to control the degradation of systems by moving to predictive maintenance (Mobley, 2002).

2.2 Predictive Maintenance Approach

Predictive Maintenance help eliminate machinery breakdown by measuring machine conditions, identifying impending problems and predicting when corrective action should be performed (Scott Franklin 1994:80).

Predictive maintenance is a condition-driven preventive maintenance program.

Instead of relying on industrial or in-plant average-life statistics (i.e., mean-time-to - failure) to schedule maintenance activities, predictive maintenance uses direct monitoring of the mechanical condition, system efficiency, and other indicators to determine the actual mean-time-to-failure or loss of efficiency for each machine-train and system in the plant (Mobley, 2002:5).

“Compared with reactive maintenance, condition-based (or predictive) maintenance demonstrates considerable advantages and has become the pioneering maintenance strategy in practice. When assets are critical in the business process chain, condition monitoring is a necessity for the delivery of effective preventive maintenance” (Mathew A, Zhang S, Ma L, Earle T, and Hargreaves D, 2006).

The technical basis behind this concept of predictive maintenance is that most ailing components warn that they are on the verge of failure. Warnings include changes in vibration levels, heat dissipation, noise etc.

Predictive maintenance is a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation. A comprehensive predictive maintenance management program uses the most cost effective tools (e.g., vibration monitoring, thermography, tribology) to obtain the actual operating condition of critical plant systems and based on this actual data schedules all maintenance activities on an as-needed basis. Including predictive maintenance in a comprehensive maintenance management program optimizes the availability of process machinery and greatly reduces the cost of maintenance. It also improves the product quality, productivity, and profitability of manufacturing and production plants (Mobley, 2002:5).

The common premise of predictive maintenance is that regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machine-trains and process systems will provide the data

required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine-train failures (Mobley, 2002:4).

Many authors noted that the primary focus of any predictive maintenance program must be on the critical process systems or equipment that constitutes the primary production activities of the plant.

2.2.1 Techniques

Five non-destructive techniques are normally used for predictive maintenance management: vibration monitoring, process parameter monitoring, thermography, tribology, and visual inspection. Each technique has a unique data set that assists the maintenance manager in determining the actual need for maintenance (Mobley, 2002:6).

- ***Vibration Monitoring***

All mechanical equipment in motion generates a vibration profile, or signature, that reflects its operating condition. This is true regardless of speed or whether the mode of operation is rotation, reciprocation, or linear motion.

Vibration analysis is used primarily with rotating equipment to find problems such as misalignment, out-of balance conditions, and bearing defects. Because most normal plant equipment is mechanical, vibration monitoring provides the best tool for routine monitoring and identification of incipient problems (Mobley, 2002:6).

Predictive maintenance has become synonymous with monitoring vibration characteristics of rotating machinery to detect budding problems and to head off catastrophic failure.

However, vibration analysis does not provide the data required for analyzing electrical equipment, areas of heat loss, the condition of lubricating oil, or other parameters typically evaluated in a maintenance management program (Mobley, 2002:114).

Nevertheless, the use of vibration analysis is not restricted to predictive maintenance. This technique is useful for diagnostic applications as well. Vibration monitoring and analysis are the primary diagnostic tools for most mechanical systems that are used to manufacture products. When used properly, vibration data provide the means to maintain optimum operating conditions and efficiency of critical plant systems (Mobley, 2002:117).

- ***Thermography***

Thermography serves primarily to find electrical components that are hotter than normal. Such a condition usually indicates wear or looseness. It uses instrumentation designed to monitor the emission of infrared energy (i.e. surface temperature) to determine operating condition.

Infrared technology is predicated on the fact that all objects with a temperature above absolute zero emit energy or radiation. The intensity of infrared radiation from an object is a function of its surface temperature.

- ***Tribology***

Tribology is the general term that refers to design and operating dynamics of the bearing-lubrication-rotor support structure of machinery. Two primary techniques are being used for predictive maintenance: lubricating oil analysis and wear particle analysis.

The primary applications for lubricating oil analysis are quality control, reduction of lubricating oil inventories, and determination of the most cost-effective interval for oil change.

Wear particle analysis is related to oil analysis only in that the particles to be studied are collected by drawing a sample of lubricating oil. Whereas lubricating oil analysis determines the actual condition of the oil sample, wear particle analysis provides direct information about the wearing condition of the machine-train. Particles in the lubricant of a machine can provide significant information about the machine's condition. This information is derived from the study of particle shape, composition, size, and quantity.

- ***Process parameter monitoring***

Process inefficiencies, like the example, are often the most serious limiting factor in a plant. Their negative impact on plant productivity and profitability is often greater than the total cost of the maintenance operation. Without regular monitoring of process parameters, however, many plants do not recognize this unfortunate fact.

According to Mobley (2002), a comprehensive predictive maintenance program should include routine monitoring of process parameters.

- ***Visual Inspection***

Visual inspection was the first method used for predictive maintenance. Almost from the beginning of the Industrial Revolution, maintenance technicians performed daily “walk-downs” of critical production and manufacturing systems in an attempt to identify potential failures or maintenance-related problems that could impact reliability, product quality, and production costs.

Regular visual inspection of the machinery and systems in a plant is a necessary part of any predictive maintenance program. Routine visual inspection of all critical plant systems will augment the other techniques and ensure that potential problems are detected before serious damage can occur (Mobley, 2002).

2.2.2 Benefits and Prospects

Predictive technologies help eliminate machinery breakdown by measuring machine conditions, identifying impending problems and predicting when corrective action should be performed (David, 1994: 80).

Furthermore, Alligan J (2006) noted that predictive maintenance programs can streamline maintenance practices, reduce unnecessary repair/ replacement costs, avoid equipment failures and system outages, and improve system reliability.

Predictive maintenance method benefits include:

- ***Production availability increases:*** Since the condition of plant equipment is known, repairs can be planned and carried out without interrupting production activities.
- ***Less emergency work is performed:*** Emergency work orders will be reduced a small fraction of total work orders and overtime.
- ***Product quality is improved:*** Product quality is often worsened by mechanical degraded equipment. However, with predictive maintenance program, the mechanical condition of equipment is tracked. The data is used to determine need for maintenance on equipment before the condition affect product quality.
- ***Safety is enhanced:*** Unnecessary open inspections are eliminated, as is extensive repair work necessitated by catastrophic failure. In addition, maintenance activities are anticipated, planned and carried out in a non-emergency environment. This reduces workers' exposure to hazardous conditions.
- ***Energy savings can be substantial:*** Predictive maintenance provides several potential areas for energy savings. According to David (1994), eliminating high-energy vibration sources, can reduce machine power consumption by 10% to 15%.
- ***Inventory Cost is reduced:*** Predictive maintenance reduces inventory costs because, as substantial warning of impending failures is provided, parts can be ordered as required, rather than keeping a large backup inventory.
- ***Life of plant items is extended:*** Using a predictive maintenance program, machines are only dismantled when necessary, so the frequency of equipment disassembly is minimized, and thus the probability of '*infant mortality*' is reduced.

- **Maintenance cost is reduced:** As equipment is only repaired when needed (as opposed to routine disassembly), maintenance staff have more satisfying and worthwhile work and the costs of maintaining the machinery are reduced as resources (labour, equipment and parts) are only used when needed.

2.2.3 Extending Predictive Maintenance Program Benefits

Mobley (2002:10) noted that too many of the predictive maintenance programs that have been implemented have failed to generate measurable benefits. These failures have not been caused by technology limitation, but rather by the failure to make the necessary changes in the workplace that would permit maximum utilization of the predictive tools.

Mobley (2002) stressed that the first change that must take place is to change the perception that predictive technologies are exclusively a maintenance management or breakdown prevention tool. He further pointed out that although this function is important, predictive maintenance can provide substantially more benefits by expanding the scope or mission of the program.

The author concludes that predictive maintenance program should be extended to be used as a *Plant Optimization tool* and a *Reliability Improvement tool*. In these broader scopes, predictive maintenance programs will improve focus on eliminating unnecessary downtime, scheduled and unscheduled; eliminating unnecessary preventive and corrective maintenance tasks; extending the useful life of critical systems; and reducing the total life-cycle cost of these systems.

Plant Optimization Tool: Predictive maintenance technologies can provide even more benefit when used as a plant optimization tool. For example, these technologies can be used to establish the best production procedures and practices for all critical production systems within a plant. Few of today's plants are operating within the original design limits of their production systems. Over time, the products that these lines produce have changed. Competitive and market pressure have demanded increasingly higher production rates. As a result, the operating procedures that were appropriate for the as-designed systems are no longer valid. Predictive technologies can be used to map the actual operating conditions of these critical systems and to provide the data needed to establish valid procedures that will meet the demand for higher production rates without a corresponding increase in maintenance cost and reduced useful life. Simply stated, these technologies permit plant personnel to quantify the cause-and effect relationship of various modes of operation. This ability to actually measure the effect of different operating modes on the reliability and resultant maintenance costs should provide the means to make sound business decisions (Mobley, 2002:15).

Reliability Improvement Tool: As a reliability improvement tool, predictive maintenance technologies cannot be beaten. The ability to measure even slight deviations from normal operating parameters permits appropriate plant personnel (e.g., reliability engineers, maintenance planners) to plan and schedule minor adjustments that will prevent degradation of the machine or system, thereby eliminating the need for major rebuilds and associated downtime (Mobley, 2002:16).

2.2.4 Evidence of Increased Industrial Application of Predictive Maintenance

The addition of a comprehensive predictive maintenance program can and will provide factual data on the actual mechanical condition of each machine-train and the operating efficiency of each process system. This data provides the maintenance manager with actual data for scheduling maintenance activities (Mobley, 2002:5).

Predictive maintenance using process efficiency, heat loss, or other non-destructive techniques can quantify the operating efficiency of non-mechanical plant equipment or systems. These techniques used in conjunction with vibration analysis can provide maintenance managers and plant engineers with information that will enable them to achieve optimum reliability and availability from their plants (Mobley, 2002:6).

A survey performed by Michael Korf in the 2002 timeframe queried managers who had managed the implementation of multiple advanced maintenance strategies over the past ten year period. They were asked to objectively rank the impact of implementation. The results (*Figure 2.3*) show that a properly implemented Predictive Maintenance program achieved better results than such heavy weights as Reliability Centred Maintenance (RCM), and Total productive Maintenance (TPM).

Furthermore, data based on feedback from predictive maintenance users in various industries collected by Michael Korf also shows (*Figure 2.4*) the industry return on investment in predictive maintenance implementation in the surveyed industries. The author noted that heavy industries with extremely critical equipment showed the best returns. *Note the horizontal axis on the chart represents return on investment in multiple of millions dollar.*

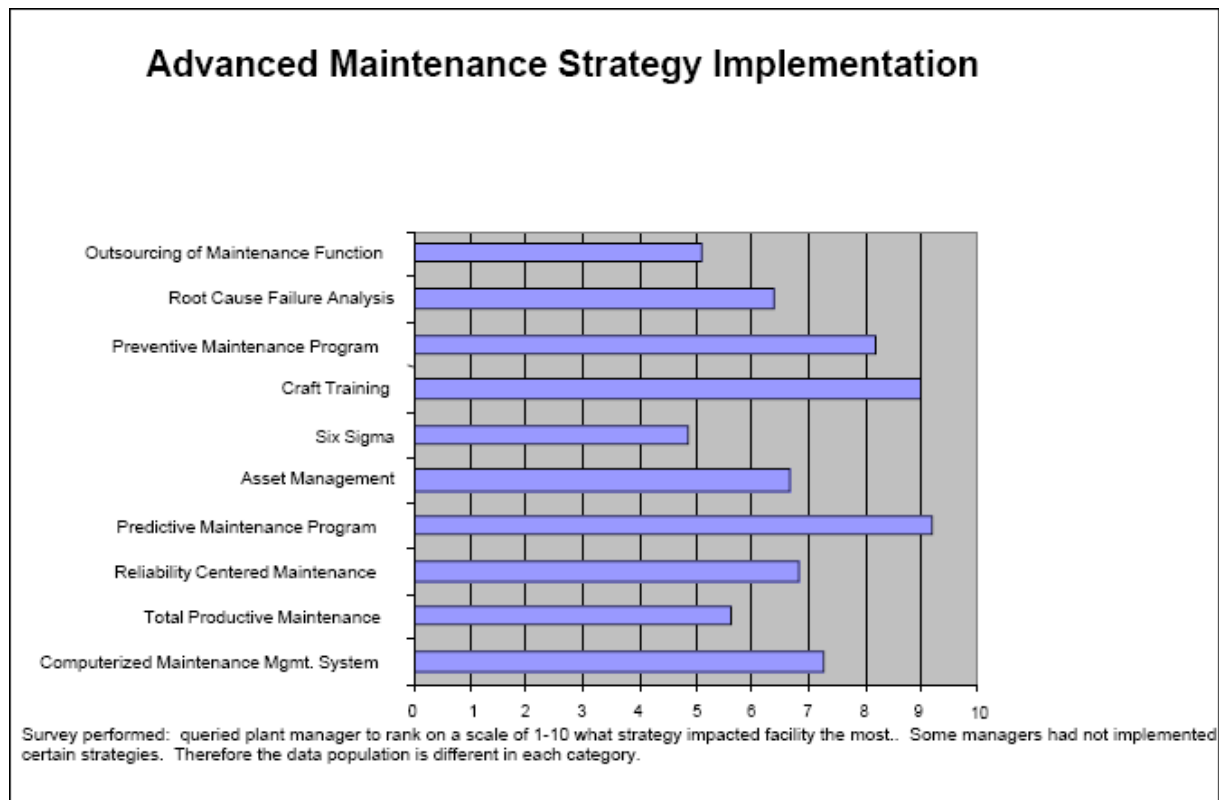
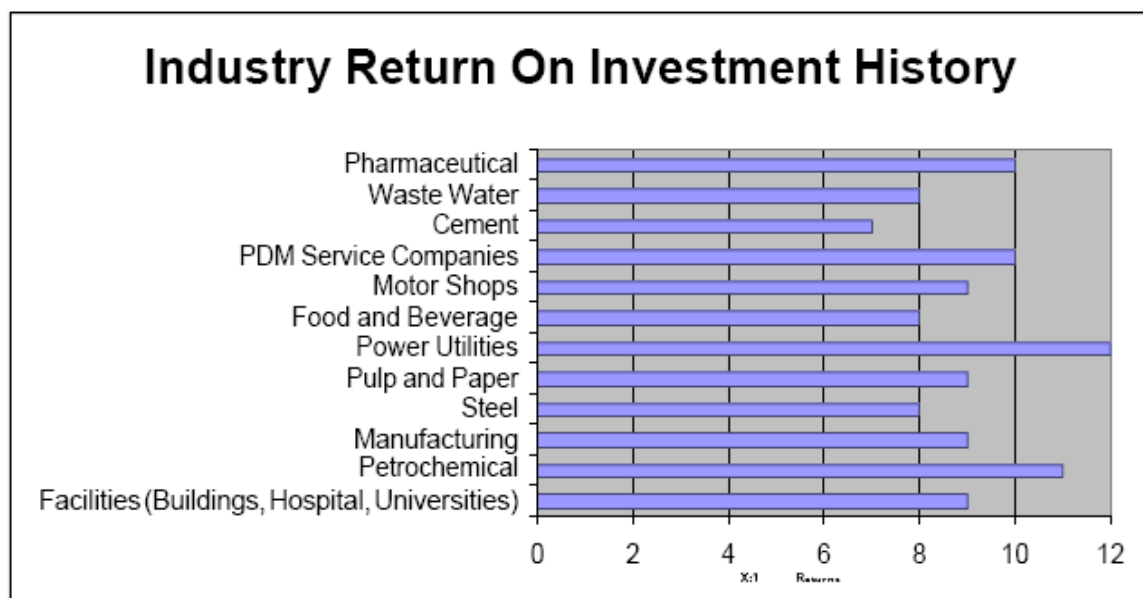


Figure 2.3 Advanced Maintenance Strategy Implementation (Courtesy Michael K, 2000)



Data collected from PDM users 2001-2004

Figure 2.4 PdM Implementation Return On Investment (Courtesy Michael K, 2002)

Finally, the survey on the outlay of improvement returns on investment through implementation of effective predictive maintenance program produced the chart in the figure below.

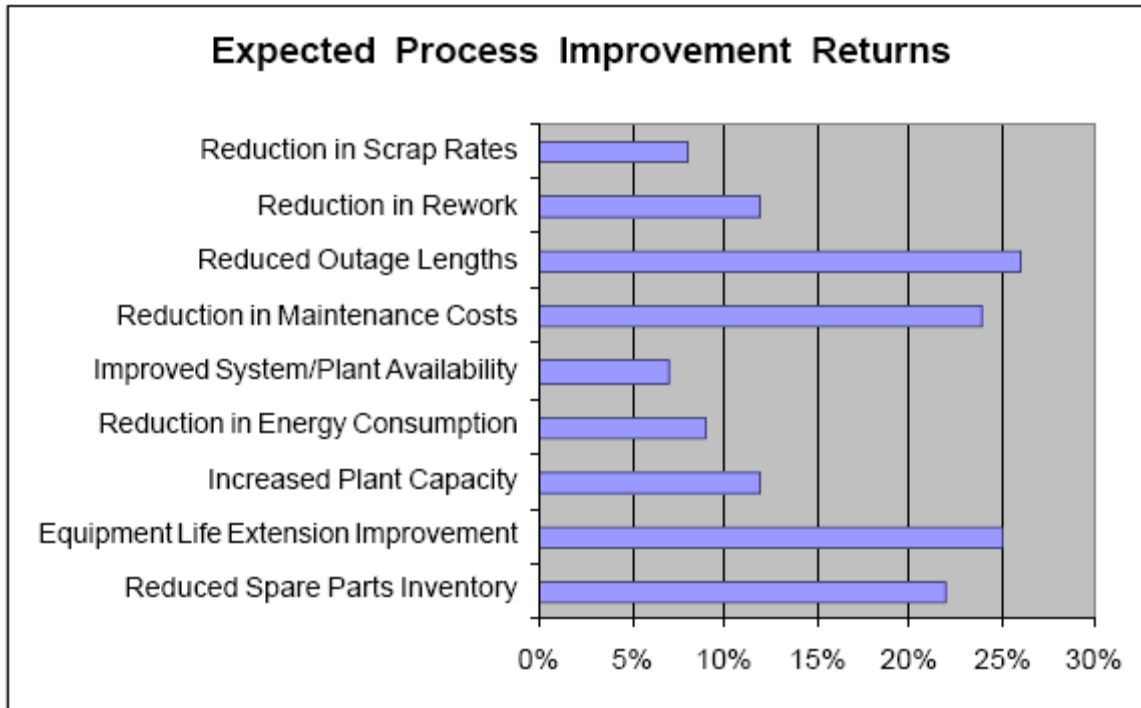


Figure 2.5 PdM Implementation Process Improvement Returns (Courtesy Michael K, 2002)

In fact, other independent surveys by Sullivan et al (2010) indicate the following industrial average savings resultant from initiation of a functional predictive maintenance program:

- Return on investment: 10 times
- Reduction in maintenance costs: 25% to 30%
- Elimination of breakdowns: 70% to 75%
- Reduction in downtime: 35% to 45%
- Increase in production: 20% to 25%.

2.2.5 Predictive Maintenance Systems

Mobley (2002:355) noticed that predictive maintenance systems should provide the ability to automate data acquisition, data management, trending, report generation, and diagnostics of incipient problems, but the system should not be limited to this technique alone.

Leger J, Neunreuther E, Lung B and Morel G (1998) also explained that predictive maintenance strategy is based on *condition monitoring, diagnosis and prognosis*. The authors further stressed that predictive maintenance programs must satisfy the whole functionalities related to the dynamic of degradation (*monitoring, diagnosis, prognosis, decision, compensation, correction, execution*) of equipment.

The authors stressed that at the heart of any successful Predictive maintenance System are the three functions:

- **Monitoring** produces a degradation value and its behaviour type from observation. The behaviour type of degradation is relevant to understand in what kind of abnormal behaviour the system is.
- **Diagnosis** produces the cause of this degradation from its value and type. Diagnosis needs observation to correlate observation and degradation cause hypothesis.
- **Prognosis** produces the effect of this degradation from its value, its type, and the degradation cause.

These three functions allow elaborating relevant information to take a decision on the action to be applied. From this decision, the other three functions *Compensate, Correct and Execute* to produce the action order towards maintenance agent. The

overall predictive maintenance system based on the work of Leger J et al is depicted in Figure 2.6.

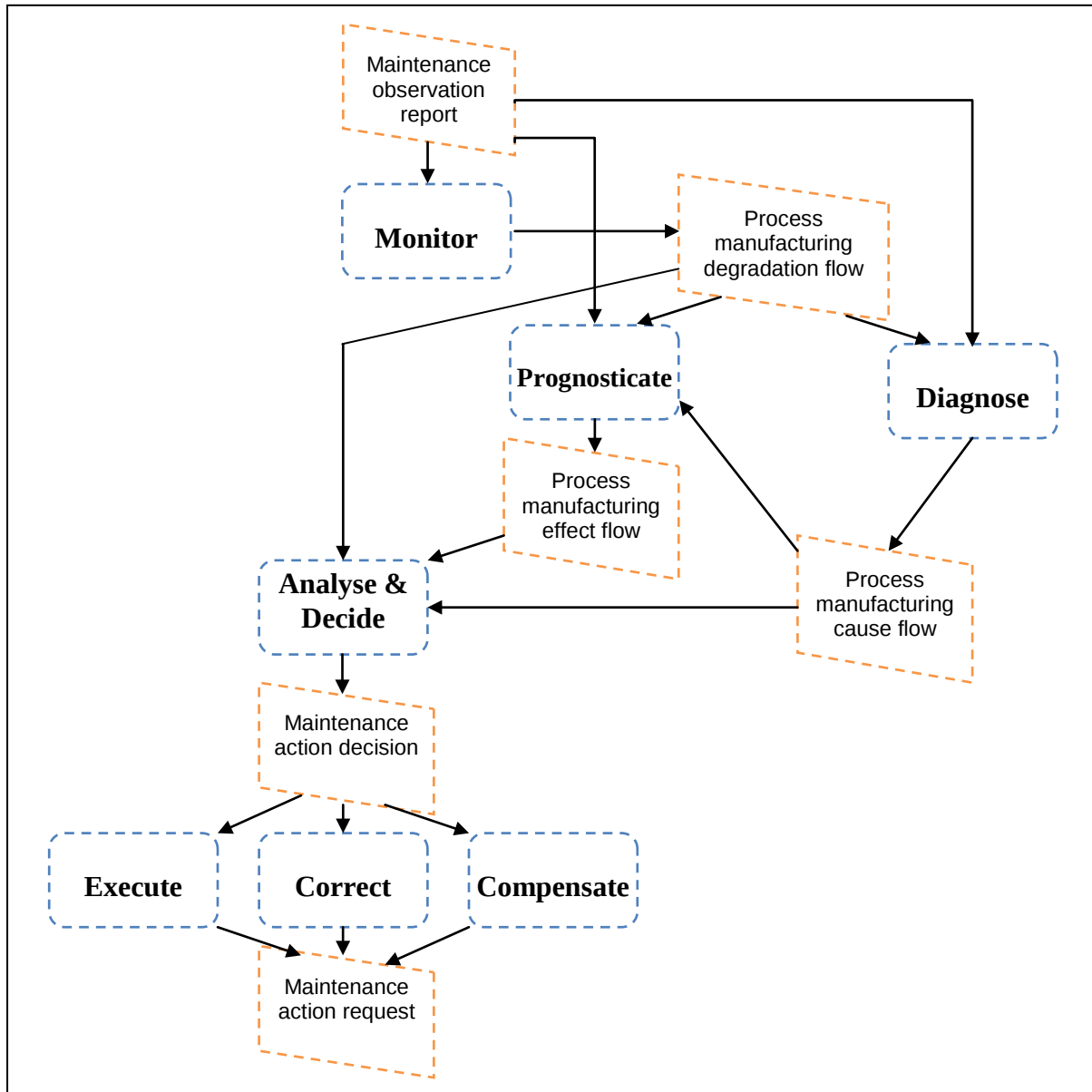


Figure 2.6 *Process model of Predictive maintenance System* (Courtesy Leger J et al (2007))

Mathew A, Zhang S a, Ma L, Earle T, and Hargreaves D (2006) in their work provides a similar structured process chain for effective predictive maintenance for any

business requirements. The process chain defines what processes/ systems are required to support predictive maintenance, and the information resources utilised.

The authors further structure the process steps to six logical steps (*Figure 2.7*):

1. **Monitoring:** The first process in the chain is acquiring data about the condition of an asset through sensors. According to Mathew A, Zhang S a, Ma L, Earle T, and Hargreaves D (2006), sensor technology has matured over the years, and many monitoring techniques are now possible. Vibration, current signature, temperature, pressure, oil composition, and thermography are all proven analysis techniques that are available to maintenance engineers.
2. **Diagnosis:** This process involves processing and analyses of signal data from the sensors by the *condition monitoring system* to determine the condition of the asset. The analysis can determine deterioration from the original healthy state by comparison to an initial baseline. Determination of an unhealthy condition is followed by a *fault diagnosis* to trace the root cause (Mathew A, Zhang S a, Ma L, Earle T, and Hargreaves D, 2006).
3. **Prognosis & Decision Making:** This process step involves calculating the reliability and the business maintenance objective to predict maintenance requirements. “By understanding the past and present condition of an asset, a judgement about its reliability can be provided. The reliability of the asset provides an indicator to the health of the asset, and can be used to predict when failures will occur (i.e. *prognosis*). Combining this information with a company’s maintenance strategy allows the system to optimise the maintenance plan” (Mathew A, Zhang S a, Ma L, Earle T, and Hargreaves D, 2006).

4. **Issuing maintenance work orders:** Once a condition-based maintenance plan is developed, work orders can be generated by the CMMS. This action will allocate resources to the maintenance work order, schedule operations, and organise documentation.
5. **Managing the maintenance process:** Subsequent management of the maintenance work is conducted by the CMMS for management of inventory and budgets.
6. **Updating the financial information:** Cost information, such as resources and inventory consumed, capital expenditure, wages accrued, and incidentals are passed onto the enterprise resource system for financial reporting.

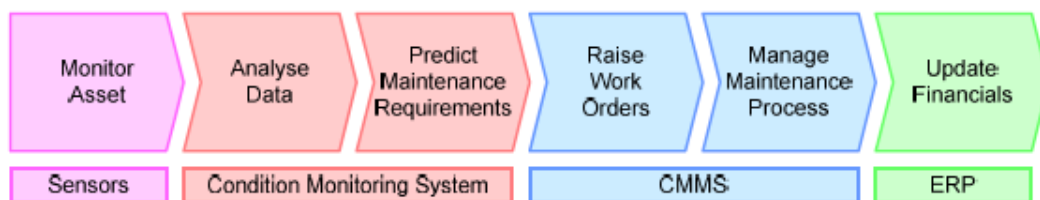


Figure 2.7 Optimized Predictive Maintenance process chain

The authors however noticed that the process chain sits in the condition monitoring section (*diagnosis, prognosis, and decision making*) covering the data analysis and maintenance prediction process.

In conclusion, the authors noted that an accurate maintenance decision largely relies on accurate asset health prediction through the adoption of effective diagnosis and prognosis techniques.

Zhang S, Mathew J, Ma L & Sun Y. (2005), also stressed the importance of fault diagnosis to improving maintenance programs. According to the authors, “fault diagnosis can assist in the discovery of the fault severity, root cause, and subsequent guidance in enhancing maintenance”.

2.3 Fault Diagnosis: Introduction

As manufacturing processes become more complex, the monitoring of manufacturing processes is gaining importance to assess process performance and improve process efficiency and product quality (Q. Peter He, S. Joe Qin, and Jin Wang, 2005).

Early detection of faults can help avoid system shut-down, breakdown and even catastrophes involving human fatalities and material damage. A system which includes the capacity of detecting, isolating, identifying or classifying faults is called a fault diagnosis system (Patton R, Uppal F and Lopez-Toribio C, 2001).

After a fault has been detected, fault diagnosis becomes important because it is desirable to find the root cause of the fault. Q. Peter He, S. Joe Qin, and Jin Wang (2005) describe fault diagnosis as the next important task after fault detection in process monitoring.

Fault diagnosis can be viewed as the process of linking symptoms to causes, paralleling the field of medical diagnosis (Becraft et al, 1993). Thus, the goal of process fault diagnosis is to match patterns of sensor measurements and process

alarms (the symptoms) to specific equipment malfunctions and operational faults (the causes).

Sobhani E and Khorasani K (2009) described a “fault diagnosis system” as a system that has the ability to detect the presence of faults in a system under monitoring, determine their locations, and estimate their severities. In other words, a fault diagnosis system is capable of performing three tasks of *detection*, *isolation*, and *identification* of faults, which are defined as follows:

- **Fault detection:** to make a binary decision whether everything is fine (nominal) or something has gone wrong (off-nominal).
- **Fault isolation:** to determine the location of the fault, i.e., to identify which component, sensor, or actuator has become faulty.
- **Fault identification:** to estimate the severity, type, or nature of the fault.

Sobhani E and Khorasani K (2009) concluded that the relative importance of the three tasks highly depends on the application and the objective of having a fault diagnosis system. “However, the detection is essential for any practical system, isolation is almost equally important, and identification is crucial for fault recovery and reconfiguration as well as health monitoring and maintenance purposes. Furthermore, accurate identification of fault severities is an invaluable asset for system maintenance”.

There are many reasons why diagnosis is important in industrial applications. One of the reasons, according to Erik Frisk et al (2008), is that within process industry, economic factors may be of importance since unplanned stops in a production line may cost large sums of money. In addition, Angeli C (2004) noted that there is an

increased interest in plant fault diagnosis due to the growing demand for higher performance, efficiency, reliability and safety in industrial systems.

In conclusion, there is plenty of evidence that prompt fault diagnosis with a careful, well-planned predictive maintenance prolongs the life of equipment and prevents costly downtime.

2.3.1 Traditional Fault Diagnostic Approaches

Traditional approaches to fault diagnosis include fault trees-based, rule-based or case-based systems. These methods involve enumeration of faults and their association with visible features of system behaviour (Narasimhan, 2002).

Most traditional approaches to automated diagnosis used fault dictionaries or fault symptom tables to perform diagnosis. In this approach, extensive simulations are used to predict fault symptoms, which, at run time, are compared against actual symptoms to isolate faults. This approach involves building a decision tree that structures the fault analysis task as a set of questions.

Rule based approach involves the use of associational knowledge in the form of links between observed symptoms and possible causes. The knowledge is typically obtained directly from human experts. In some systems, this knowledge is expressed as production rules.

Another approach to diagnosis has been case-based diagnosis. In this approach, experiences are stored in the form of diagnostic cases. When a new case needs to

be diagnosed, stored cases are scanned to find any matches with the new case. The new case is then added to the library of stored cases under an appropriate category.

These approaches suffer from the problem that they are not really diagnosing but actually verifying a diagnosis. All behaviours of the system have already been precompiled and the diagnosis method checks if the actual behaviour confirms to one of these pre-compiled behaviours. Pre-compiling the information is not a trivial task. Every possible situation needs to be considered otherwise not all faults can be detected or the wrong fault may be detected. Therefore, these methods are not scalable. Moreover, when a new system is considered, the process of building the knowledge base has to be repeated from scratch (Narasimhan, 2002).

Furthermore, Narasimhan (2002) and many other authors noted that the traditional methods suffer from several major drawbacks. These drawbacks include:

- It is not possible to enumerate all the ways a system may fail and compile the visible symptoms for a number of faults.
- The traditional approaches require a lot of experience and time to gather fault-related information and compilation of this information in the appropriate form, from which actual diagnosis may be performed. With the need for quick turnaround in the design and deployment of modern systems, this becomes a hard task.
- Skilled human intervention is required for extracting useful information from these systems which sometimes may lead to incorrect output from the systems.

Papadopoulos Y (2003) pointed out that attempts of wider application of traditional fault diagnosis techniques to complex systems, though, have also shown limitations,

namely that such systems are also prone to inconsistencies, incompleteness, long search time and lack of portability and maintainability.

He went further to say that these problems gradually highlighted the limitations of the rule-based reasoning as a method for knowledge representation and underlined the need for more elaborate models. As a result, monitors started to emerge with the ability to solve monitoring problems by operating on functional, logical, structural or behavioural models of the system or its processes.

Papadopoulos Y (2003) concludes that experience has shown that model-based systems are more likely to be consistent, and to provide better diagnostic coverage than expert or rule-based systems, because the model building and model validation processes supply a systematic way for collecting the required knowledge about the monitored process.

Kramer M. (1991) also reported in the first international workshop on principles of diagnosis the need for new model-based frameworks for efficient interaction of behavioural knowledge and diagnostic inference was pointed out.

In recent times, Sobhani E and Khorasani K (2009) reports that monitoring and diagnostics can generally be automated with advanced decision support systems that utilize model-, rule-, and intelligent-based methodologies.

2.3.2 Model Based Fault Diagnosis

Model-Based Diagnosis (MBD) provides a better alternative to the traditional approaches by using a model of the system configuration and behaviour of the

system (Hamscher, W., L. Console, and J. De Kleer, 1992). In model-based fault diagnosis methods, the event diagnosis are almost automated which reduce human interference.

The ***model-based diagnosis***, first suggested by Reiter and later expanded more by de Kleer, Mackworth and Reiter, is the most disciplined technique for diagnosis of a variety of systems. This technique, which reasons from ***first principle***, employs knowledge of how devices work and their connectivity in form of models (Fijany A et al, 2002).

Originated in the early 70's, the model-based fault diagnosis technique has developed remarkably since then. Its efficiency in detecting faults in a system has been demonstrated by a great number of successful applications in industrial processes and automatic control systems. Today, model-based fault diagnosis systems are fully integrated into vehicle control systems, robots, transport systems, power systems, manufacturing processes, process control systems, just to mention some of the application sectors (Ding S, 2008).

The basic principle of model-based diagnosis can be understood as the comparison between a healthy system model and a faulty state behaviour of a system. The system behaviour is measured through sensors. The estimated healthy system model can be used to predict what these measurement values should be under normal conditions. The estimated healthy state value is compared to the observed value to identify any discrepancy (Console L, and Dressier O, 1999).

The initiative idea of the model-based fault diagnosis technique is to create system or process model which is implemented in the software form on a computer. A process model is a quantitative or a qualitative description of the process dynamic and steady behaviours, which can be obtained using the well-established process modelling techniques (Ding S, 2008).

A process model describes the relationship between system parameters (like pressure, temperature, flow-rate etc.) and the outputs.

The healthy process model will run parallel to the faulty process model and be driven by the same process inputs. It is reasonable to expect that the re-constructed process variables delivered by the process models will well follow the corresponding real process variables in the fault-free operating states and show an evident deviation by a fault in the process.

In order to receive this information, a comparison of the measured process variables (output signals) with their estimates delivered by the process models will then be made. The difference between the estimated healthy process variables and the measured process variable is called residual. "Roughly speaking, a residual signal carries the most important message for a successful fault diagnosis" (Ding S, 2008):

If residual does not equal 0 then fault, otherwise fault-free.

The procedure of creating the estimates of the process outputs and building the difference between the process outputs and their estimates is called residual

generation. Correspondingly, the process model and the comparison unit build the so-called residual generator, as shown in Figure 2.8.

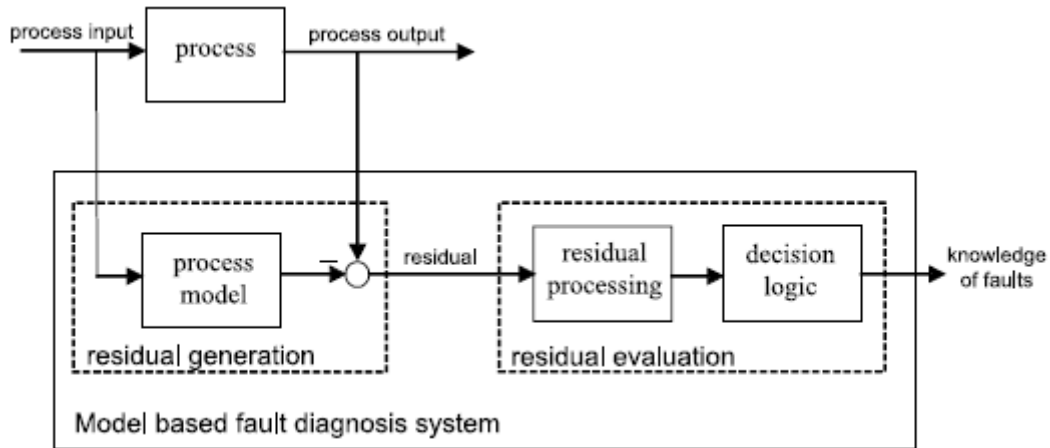


Figure 2.8 Schematic description of the model-based fault diagnosis scheme

2.3.3 Industrial Applications of Model-based Approach

Model-based reasoning has been applied to many different fields. Over the past 20 years, there has been much work done in the area of model-based reasoning and diagnosis (Console L, and Dressier O, 1999).

Electronic devices were the main application used in the early work to experiment ideas and techniques. Although electronic devices were one of the main field for experimenting ideas, most of the applications that are currently on the field come from other areas (Console L, and Dressier O, 1999).

Aerospace is an important area of application (on which many details are not disclosed). Model based diagnosis techniques have been used to automatically diagnose and mitigate failures on-board spacecraft. Among different applications, it is interesting to mention the role that model-based reasoning and diagnosis are playing

in the NASA REMOTE AGENTS project for autonomy in space. Such project includes Livingstone model based fault diagnosis and recovery system on spacecrafts (Console L, and Dressier O, 1999).

Turning to the automotive domain, there are several reasons why diagnosis (and Model based in particular) became more and more important in this field. First of all, the increasing complexity of the cars called for more sophisticated diagnostic techniques.

Secondly, legislation required the presence of diagnostic systems in the Electronic Control Unit (ECU) of the car.

Thirdly, competition between manufactures led them to investigate new features for attracting customers and for augmenting their satisfaction. Thus, the interest of car manufacturers is growing and they are looking at model-based reasoning as one way of managing the increasing complexity of cars and the high maintenance costs and unnecessary downtime deriving from such a complexity (Console L, and Dressier O, 1999).

Strauss P and Price C (2004) noted that *“the automotive industry was the first to promote the development of applications of model-based systems technology on a broad scale and, as a result, has produced some of the most advanced prototypes and products”*.

Also model based reasoning has been noted to found increased use in process, utilities and manufacturing industry as a viable industrial tool in an industrial setting Stumptner M and Wotawa F(2000).

Some notable current applications of model-based approach in different industry are cited in the article by Stumptner M and Wotawa F(2000) on “Industrial Applications of Model-based Reasoning”.

For example, the experience in TIGER (an EU founded project) originated a commercial system for the diagnosis of gas turbines that is used in several locations (Console L, and Dressier O, 1999).

Model based approach is also used to determine placement of sensor during designs of process systems (Mauss et al., 2000).

Montmain J et al (1998) in an article presents a model-based approach for industrial plant supervision. The work is based on the early detection of abnormal situations, using as example a chemical separation process that occurs as part of nuclear fuel reprocessing. The approach provides a flow-based representation framework and a working implementation as well as a multidimensional methodology for developing knowledge based systems for process operator assistance which allows explicit incorporation of the operator's viewpoint in a control setting. The approach was successfully used to tackle real-world industrial problem and demonstrates the model based reasoning provide operational solution to industrial problems.

Sachenbacher et al. (2000) present the use of model-based diagnosis for on-board diagnosis of automotive systems. The paper gives an overview of the European “Vehicle Model-based Diagnosis (VMBD)” project resulting in a prototype diagnosis system. This diagnosis system was used in a demonstrator vehicle with built-in faults for showing diagnosis capabilities.

Stumptner M and Wotawa F (2000) noted that the prototype (VMBD) has shown that the diagnosis response times required by the real-time application could be achieved and that qualitative reasoning was a useful and effective tool for modelling.

Flores and Cerda (1999) introduce an algorithm for constructing a model for a linear circuit, a class of circuits with wide applicability in engineering applications (e.g., considering again the automotive domain, most of the electrical system of a car can be represented by a linear circuit). They use the well-known star-mesh reduction together with a simple data structure to reduce time for constructing the model. This paper follows a long line of research in this domain of electrical circuits.

Milde et al. (2000) give an overview of the German research project “INDIA” (Intelligent Diagnosis in Industrial Applications) which had the aim of providing tools for making model-based diagnosis accessible for industry. The work carried out during the project and presented in the paper comprises three applications covering different tasks and application areas.

The first part shows how fault trees can be automatically generated from models and compares fault tree diagnosis performance with handcrafted models in forklift maintenance.

The second part gives an overview of tools for model-based support to diagnosis and fault analysis in the automotive industry, and the third part describes a diagnostic system for a chemical distributor used in a dye-house.

Stumptner M and Wotawa F (2000) also noted that all of the given examples in “INDIA” show how model-based reasoning can be used effectively in industry.

Furthermore, Hewlett-Packard laboratory in 1997 also reported the deployment of a prototype model-based diagnostic system, “ JADE”, in a manufacturing test process at Hewlett-Packard’s Grenoble Personal Computer Division (GPCD), the division responsible for manufacturing of Hewlett-Packard’s PC products.

“The JADE system combines a simple model-based approach to diagnosis with probabilistic reasoning. It receives the functional test results direct from the tester, and analyses these to determine which faults are most likely to have caused them” (Hewlett-Packard laboratory, 1997).

The researchers at Hewlett-Packard’s laboratory reasoned that the traditional approach to diagnosis has suffered from the fact that expertise is only developed after manufacturing has begun. The model-based approach advocates reasoning with models of the system to be diagnosed. These models can be obtained at design time.

The researchers conclude that the JADE system has produced significant benefits in productivity in the manufacturing plant of the company. The implementation of the

system resulted in dramatic performance improvements. They report that technicians with JADE were three times as productive as technicians without JADE. "This of course, gave large cost savings in manufacturing. "The direct savings resulting from improved productivity enabled by JADE was 4.5 million francs over the first year" (Hewlett-Packard laboratory, 1997).

The researchers also noticed that "the system has a very low cost of ownership compared with other approaches. The resulting systems from model based approach are easy to use and effective. Maintenance of the models is simple, requires little effort, and can be performed by test technicians familiar with the system".

After a detailed review work on different industrial application of model based reasoning, Stumptner M and Wotawa F (2000) conclude that "the applications show that model-based reasoning has made the jump from a theoretical foundation to industrial domains that range from control to embedded systems, and is now being considered in domains that are of considerable economic importance. With a variety of approaches present, we can look forward to experience from these projects then serving to foster new and challenging research issues".

Ding S, 2008 also says besides the technological and economic demands, the rapid development of the computer technology and the control theory is another main reason why the model-based fault diagnosis technique is nowadays accepted as a powerful tool to solve fault diagnose problems in technical processes (Ding S, 2008).

However, Papadopoulos Y (2003) noted that despite the substantial progress in the development of model-based systems, though, a number of open research issues still remain.

One of such issue is the re-use of models. Regassa T (2009) noticed that “the degree of re-use of models for different systems, scenarios, and purposes is very low, even when they are quite similar, and there are few libraries containing models that are context-independent. Models used for successful projects often have specificities of the task, domain, or even device compiled into them, so that they cannot be integrated into different projects even of similar nature. Another obstacle is the use of different modelling paradigms and tools that cannot be integrated”.

Furthermore, the researchers at Hewlett-Packard’s laboratory also stressed that model based approach has the disadvantage that the models required are often complex, and so can require a lot of effort to develop.

Lastly, model based fault diagnosis has find many useful application in diagnosis of technical systems; however there are increased application in medical diagnosis recently (Console L, and Dressier O, 1999).

Successful applications of model-based approach in industrial domain especially manufacturing have been demonstrated in industries in advanced countries. However, extensive literature review and interviews carried out show that there has been no effort towards development of such systems for solving industrial problems in underdeveloped countries like Nigeria.

2.4 Maintenance Practises in Nigerian Manufacturing Industry

Today's competitive environment requires that industries sustain full productive capacities while minimizing the required capital investment. From the maintenance perspective, this means maximizing equipment availability and reliability, by extending each individual component's life (Eti M., Ogaji S., Probert S., 2006).

Hence, business leaders increasingly realise the strategic importance of the maintenance function for organizations, which have significant investments in physical assets, and so is a necessary expense in the operating budget. Unfortunately, in many Nigerian industries, effective maintenance is usually not a high priority and the consequent cost of failures, as a percentage of the total cost, keeps rising. The problems are that:

- Not many senior managers have pertinent knowledge and maintenance experience.
- There is no maintenance education course in Nigeria universities
- Maintenance budgets are inadequate
- Many organizations regard maintenance as a cost centre rather than a business centre.

In recent years, some Nigerian industries have gradually shown increasing concerns about (i) higher maintenance costs and (ii) maintenance productivity. Maintenance is often the largest single management expenditure in Nigerian plants: in many industries, it exceeds the annual net profit (Eti M., Ogaji S., Probert S., 2006).

Pascal and Athos (2002) stressed that businesses today need innovation, to break the inherent moulds of perception and redundant patterns of behaviour. Organizations should be changing from a repair focused to reliability-focused culture.

According to Eti M., Ogaji S., Probert S., (2006), to increase equipment uptime in Nigerian manufacturing industry, a proactive profit-focused approach is needed to narrow the gap between actual costs and ideal costs. Also Robert (2002) and Hughes (2002) both suggested that the goal of any maintenance practices should be to minimise the frequency and magnitude of emergencies and unscheduled maintenance.

2.4.1 Challenges of the Nigerian Manufacturing Industry

Implementation of proactive maintenance practise is perhaps preferable to the present reactive maintenance practice which is still prevalent in Nigeria industries. However, Eti M., Ogaji S., Probert S., (2006), noted that less than 1 percent of the maintenance managers in Nigerian manufacturing industries understand the effectiveness of proactive maintenance programmes compared to reactive maintenance. Furthermore, several problems have been identified by various authors for the lack of interest in implementation of proactive maintenance in the Nigerian Manufacturing industry. Summarily, some of the pertinent problems identified include:

- Maintenance is not regarded seriously even at local management level
- Maintenance lacks a business culture (e.g. undertaken without business plans, ineffective budget allocation; and unfocused reports produced.)
- Maintenance supervisors and team leaders frequently lack management skills.
- Maintenance often remains isolated, with little integration with the functions of other departments (e.g. production)

- Only low levels of planned maintenance are implemented.

Furthermore, Yam, Tse and Tu (2001) reasoned that high maintenance costs in industrial firms highlight the need to enhance modern maintenance practices, and to use intelligent computer-based maintenance systems.

Hence, with increased application of model-based reasoning to solving industrial problems in developed company, it is necessary for Nigerian industry to seek similar approach to solving its peculiar problems in order to improve its competitiveness in the global market and enhance its bottom lines.

2.5 Summary

Chapter 2 presents excerpts from relevant existing literature and adequately provides a basis for understanding predictive maintenance and model-based fault diagnosis concepts.

The research methodology and designs adopted for this dissertation are presented in the next chapter.

3. Empirical Investigation

Chapter 3 presents a detailed explanation of the research design and methodology and provides insight into how the research was conducted.

3.0 EMPIRICAL INVESTIGATION

3.1 *Research Overview*

Primarily, this research is focused on how to reduce downtime in the Nigerian manufacturing industry, through the effective implementation of an enhanced predictive maintenance strategy. To achieve this objective, several methods were employed in carrying out this research. Basically, this chapter introduces practical methods by which this research work was carried out.

3.2 *Research Approach*

The objective of this research is centered on the research problem that needs to be defined and analyzed in the manufacturing industries in Nigeria.

Hence, this research is focussed on the need of companies in the manufacturing industry in Nigeria. The foundation of the research will depend on case studies of companies in the manufacturing industry in Nigeria.

The research specifically target companies in the manufacturing industry that have implemented a predictive maintenance strategy with or without condition monitoring system such as model based fault diagnosis system. For the purpose of this research, five manufacturing companies in Nigeria were selected.

Adequate literature review, web-sourced information and news articles were used to obtain adequate understanding of the problem necessitating the more conclusive scientific study in this research.

Research questions were developed through the preliminary study of existing work on practises of predictive maintenance approaches and were used to carry out personal interviews. The research will then involve deployment of a prototype of the new framework in a small manufacturing company in Nigeria for a period of six weeks. The data that shall be presented in this research report shall be the result of the preliminary interview and the test in the manufacturing industries in Nigeria.

For the purpose of the research work, one primary research problem that needs to be defined and analysed in the manufacturing companies in Nigeria:

Can inclusion of automated model-based fault diagnosis in predictive maintenance programs reduce the spate of incessant downtime in manufacturing companies in Nigeria?

Hence, in order to completely define, analyze and solve this problem, a few research questions are addressed. These questions (stated below) will be the main focus of this study.

- 1. Do the current implementations of predictive maintenance programs in Nigerian manufacturing Industries involve adequate automated condition monitoring systems (monitoring, diagnosis, and prognosis)?*
- 2. Can implementation of automated condition monitoring system (model-based) in Predictive Maintenance program assists in improving equipment availability in the manufacturing industries in Nigeria?*

The outcomes of this research will be validated against proven theories. To further validate the research findings a computer based implementation of a prototype of the new framework will be deployed over a period of six weeks in a small manufacturing company in Nigeria. The company selected for this experimental deployment is *Rommy Poly-Products Nigeria Limited* in Lagos, Nigeria.

Also, intensive analysis, assessment, and documentation of results and findings will be employed to achieve the objectives of this research.

3.3 Primary Data Collection Method

This section presents methods and procedures adopted in gathering data for this dissertation.

3.3.1 Case studies

According to H. Odum (2003), "The case study method is a technique by which individual factor whether it be an institution or just an episode in the life of an individual or a group is analysed in its relationship to any other in the group.

Feagin, Orum, and Sjoberg (1991) describe the case study method of research as an ideal research methodology for carrying out a holistic and in-depth investigation on a research problem.

Furthermore, according to Tellis (1997), "Case studies are multi-perspectival analyses." This means that the researcher considers not just the voice and perspective of the actors, but also of the relevant groups of actors and the interaction between them.

Following the above description of case study method, this research is based on case studies of five carefully selected manufacturing companies in the industrial hub of Nigeria. The case studies identified were carefully selected to ensure similar operations and business environments. Furthermore, four of the selected companies are listed on Nigerian Stock Exchange. The five companies selected for the case studies are:

- Poly products Nigeria Plc
- Mouka Foam Nigeria Plc
- Nigerite Nigeria Limited
- CAP Plc
- Rommy Poly Products Nigeria Limited

The case study adopted for deployment and test of the framework is one of these five case studies. Four out of the five companies are indigenous manufacturing companies.

3.3.2 Selecting the Pilot plant

A manufacturing company, Rommy Poly Products Nigeria Limited, was chosen for deployment of a prototype of the new framework because:

- The company has been visited.
- Its core business, manufacturing, is the same as that of the selected manufacturing company.
- The company is a small indigenous manufacturing company in Nigeria.
- System models for the process can easily be built.

- More accurate result can be obtained because of the small size of the company.

3.3.3 Personal Interview

The use of interview was employed effectively in getting information concerning implementation of predictive maintenance program in the selected manufacturing companies. All interviews conducted in the selected companies are to get views on the following questions.

- *How has implementation of Predictive Maintenance impacted on equipment availability in your organization?*
- *Does predictive maintenance implementation receive adequate commitment from the management of your organization?*
- *What are the perceived gaps to implementation of effective Predictive Maintenance in your organization?*
- *Are personnel from production involved in current implementation of predictive maintenance program?*
- *Is there a separate group (e.g. Reliability Team) that oversees the implementation of predictive maintenance program in your organization?*
- *Does the company involve a condition monitoring system in the current implementation of Predictive Maintenance?*

The target respondents for these interviews were mainly maintenance managers of the selected companies. Although it was very difficult to have oral interview with managers in Nigerian corporate environment yet the major views received proved to be very helpful. The feedback and findings from the interviews are discussed in the next chapter.

3.4 Existing implementation of Predictive Maintenance in the manufacturing industry

To optimize maintenance it is important not only to examine the maintenance processes, but also the management approach, work culture, skill set, motivation of the work force, and the effective use of the technologies (IAEA Publication, 2007).

Hence, the companies selected for the case study were investigated to identify issues and gaps associated with implementation of predictive maintenance.

Variances will be highlighted and drawn under the following sub-sections:

- *Management and work culture*
- *Maintenance Processes*
- *People Skills/ Human resources*
- *Technologies*

3.4.1 Management and Work Culture

Management and work culture in relation to maintenance practices will be investigated in the selected companies for the case studies.

Issues concerning the management goals and plans on predictive maintenance implementation as well as corporate performance target and assessment, and continuous improvement effort will be identified.

Findings based on the outcomes of the empirical investigation will be highlighted in *chapters 4 and 5* of this dissertation.

3.4.2 Maintenance Processes

The implementation of maintenance processes will be investigated in the companies selected for case studies.

The effectiveness of maintenance work identification, control, execution and closeout will be investigated. Furthermore, various tools for carrying out the maintenance process will be examined.

Issues identified in the companies selected for the case studies will be highlighted in *Chapter 4 and 5* of the dissertation.

3.4.3 People Skills/ Human resources

Human resource productivity is a recognized indicator for organizational performance. It can be used for comparing a company with its past or goals. Also, it can be used for comparing two or more organizations (Shasfand S, and Jafarian R, 2005).

The level of awareness and knowledge among maintenance personnel on modern implementation of predictive maintenance will be investigated.

Furthermore, issues relating to training and qualification of maintenance personnel will be investigated.

Issues identified in the companies selected for the case studies will be highlighted in *Chapter 4 and 5* of the dissertation.

3.4.4 Technologies

The application of maintenance management systems (CMMS), condition monitoring technology and reporting tools in the manufacturing companies will be investigated.

The existence and effectiveness of these applications in the manufacturing environment will be highlighted from the research findings.

Issues identified in the companies selected for the case studies will be highlighted in *Chapter 4 and 5* of the dissertation.

A notable issue that will be examined here is the existence or inexistence of condition monitoring system (automated fault diagnosis system) in the current implementation of predictive maintenance.

3.5 Secondary Data

Secondary data or source of information is very vital for any research work as it will help to reconfirm or proffer answers to research questions (Saunders et al 1997). All the studies organisations had websites and information about the companies was obtained.

The primary and secondary data were comprehensive enough to supply information to make logical and balanced assessments and conclusions on the research.

3.6 Recommendations for Improving Predictive Maintenance Practices in the Manufacturing Companies in Nigeria

According to DiGiovanni (2000) in an article titled “Make the most of Predictive Maintenance”, he noted that the key to achieving an effective predictive maintenance

program is to take an integrated approach. He stressed that more attention should be paid to maintenance processes as well as cultural change.

Furthermore, Bessen (2010) also noted that technology can enhance a maintenance program but will never replace good planning and a competent crew. He added that to ensure an effective predictive maintenance program, it may be desirable to train and equip maintenance employees in an organization.

In conclusion, the proposed methods to improve predictive maintenance implementation in the Nigerian manufacturing industry will involve improvement of the 4 key elements vital to effective maintenance practice. This will be discussed in *Chapter 4 & 5*.

Change in Management and Work Culture: Creating a positive work environment that promotes a learning organization optimizes plant maintenance (IAEA publication, 2007).

This can be accomplished by: setting goals; providing strong leadership; promoting good communication; establishing an organization where individuals know their roles and responsibilities and are held accountable; and, providing the means to learn from the staff's experiences. Metrics are tracked for the purpose of understanding the areas where improvement opportunities exist and are corrected.

The result and findings of the research conducted as well as data analysis of data and information will be used to make recommendation on Management and work culture in *Chapter 5*.

Improve Maintenance Processes: Using the industry's best maintenance practices to minimize the impact on production and to maximize the workforce utilization optimizes plant maintenance (IAEA publication, 2007).

This can be accomplished by identifying work at the right time so it can be prioritized, planned, scheduled, and performed. Work is documented and reviewed to learn from the experience. These processes include day-to-day work, both planned and unplanned outage work and work resulting from proactive activities such as engineering projects.

The result and findings of the research conducted as well as data analysis of data and information will be used to make recommendation on Maintenance processes in *Chapter 5*.

Develop Maintenance personnel Skill: Plant maintenance is optimized by developing a highly motivated, qualified and skilled workforce, and a safe work environment (IAEA publication, 2007).

This can be accomplished by providing an effective training and qualification programme, and by implementing a human performance initiative that stresses positive behaviours and values.

The result and findings of the research conducted as well as data analysis of data and information will be used to make recommendation on Personnel skill in *Chapter 5*.

Apply Modern Technologies: Plant maintenance is optimized by utilizing cost effective technologies that maximize maintenance process efficiencies, provides timely information on equipment condition, and captures the lessons learned. Integration technologies are incorporated that allow access to multiple plants and department data sources, and allow the findings, recommendations, and corrective actions to be shared. Examples of technology tools are the CMMS, Process Data (PI/PHD), enterprise-wide data sharing software, and a number of condition monitoring technologies and their supporting software (IAEA publication, 2007).

A notable condition monitoring tool already discussed is the Model based fault diagnosis approach. A simplified version of the tool will be deployed in one of the companies for case studies to validate its performance and implementability. The algorithm for the implemented model based fault diagnosis system will be presented in Appendix A.

The result and findings of the research conducted as well as data analysis of data and information will form basis for recommendation on application of modern technologies to Predictive maintenance programs in *Chapter 5*.

A framework will be developed to use advances in model-based fault diagnosis technology to improve effectiveness of predictive maintenance programs and aid in decision support for maintenance processes in manufacturing companies in Nigeria.

3.7 Summary

Chapter 3 provides a comprehensive discussion of the empirical research methodology and data collection approach used for this dissertation.

The detailed results and findings of the research conducted including the analysis of the data and information gathered for this dissertation are presented in the next chapter.

4. Results and Findings

Chapter 4 presents the results and findings of various interview and experimental test conducted in some selected manufacturing companies in Nigeria.

4.0 RESULTS AND FINDINGS

In chapter 3 a detailed research methodology and design used in this dissertation was presented. Chapter 4 presents the results and findings obtained from the research. The results and findings documented are based on five case studies of manufacturing companies based in the industrial hub of Nigeria.

This chapter, therefore, contains feedback obtained from various interviews conducted in the five manufacturing company pertaining to their present practices of predictive maintenance. Furthermore, a section of this chapter documents the result obtained from deployment of a prototype model-based diagnostic program to aid the practice of predictive maintenance in one of the manufacturing companies in the case studies.

4.1 Case Studies

4.1.1 Case Study A: Mouka Limited

Mouka Limited was established in 1972. The company specialises in the manufacturing of top quality mattresses, sheeting, Pillows, Polyurethane blocks and other foam materials for industrial use. "Situated in the heart of the largest industrial estate in sub-Sahara Africa, **Mouka foam** factory is currently the largest single plant in West Africa. In 1992, Mouka decided to adhere to the Montreal Protocol and to the elimination of all Ozone Depleting Substances (ODS) from its manufacturing processes. As an organization that is conscious of its responsibility to the environment, Mouka became the first plant in Africa, Middle- East, Near- East and Eastern Europe to comply with the worldwide ban on the Ozone Depleting Substances". This and many other feats has culminated in the Mouka been awarded many ISO standard certificates (<http://www.mouka.com/>).

Mr Ade Ajayi (a Maintenance Supervisor in Mouka Limited: Interviewed June 10, 2010).

Ade Ajayi affirmed that:

- The practice of predictive maintenance in the company is still at its development phase. The practice still basically involves routine lubrication of bearings and cleaning of filters. There is no significant evidence that the implementation has improved equipment availability in the company.
- The practice basically depend on visual inspection carried out by senior maintenance personnel and does not involve the use of any diagnostic tool.

Further investigation through semi-structured interview of operations and maintenance personnel of the company revealed that:

- Breakdown of major manufacturing equipment is still rampant in the company. There is a huge backlog of maintenance work as well as scrap engine in the maintenance yard of the company.
- The management is not seriously committed to the implementation of predictive maintenance in the company.
- There is a lack of link between maintenance personnel and production technicians in provision of data used for making decisions in the current predictive maintenance program in the company.
- The company does not use any condition monitoring system in the current implementation of predictive maintenance. Maintenance activities normally involve trial and error to arrive at the root cause of a breakdown.

- Senior maintenance managers lack detail knowledge on the application, implementation and importance of predictive maintenance in a manufacturing organization.
- There is no serious effort by management of the company in equipping the maintenance personnel, especially junior staff, with necessary knowledge of modern maintenance practices through training.

4.1.2 Case Study B: Nigerite Limited

Nigerite Limited, a member of Etex Group, is the largest company in Africa engaged in the manufacturing of NT fibre cement roofing and ceiling sheets, concrete roofing tiles and vinyl floor tiles. The company is located on a fifty-acre site along Oba Akran Avenue, Ikeja, Lagos State. The company consists majorly of three production factories.

Nigerite Limited was incorporated in Nigeria in 1959 but began its commercial operations in early 1961. “Nigerite Limited is a socially responsible company and as such, keeps a close watch on the environment in line with its motto: *Towards Environmental Excellence through responsible care*” (<http://www.nigeritelimited.com/history.htm>).

Engr. Adegbola Shittu (a Maintenance Manager in Nigerite Limited: Interviewed June 15, 2010).

Engr. Adegbola Shittu stated that:

- The practice of predictive maintenance in the company is still rudimentary and has not had any significant impact on equipment availability and performance.

- Cost of procuring modern predictive maintenance tools or securing an online diagnostic service is one of the major factors hindering the implementation of predictive maintenance program in the company.

Further investigation through semi-structured interview of operations and maintenance employees of the company revealed that:

- Management of the company are not seriously disposed to the implementation of predictive maintenance because they still see it as a cost centre rather than a business centre.
- There is currently intermittent breakdown of equipment which normally result in immense production loss, and inability of the company to meet its customer demand.
- Incessant waste resulting from failure in production process is a major factor responsible for high production cost in the company, and consequently inability of the company to compete favourably with imported roofing.
- There is no conscious effort by the management to bring its maintenance personnel up in terms of training or skill development.
- The company still maintain a huge inventory of machine spares to cope with incessant breakdown of machinery in the plant.
- The company is presently not considering securing of online diagnostic services to cope with its barrage of equipment failure because of the cost and infrastructural requirement of such services.
- Accuracy of decisions resulting from present practice of predictive maintenance is low. There is a barrage of maintenance backlog and repeated failure of equipment in the company.

4.1.3 Case Study C: CAP Plc Limited

“Chemical and Allied Products Limited evolved from the world-renowned British multinational Imperial Chemical Industries plc, which formalized its Nigerian operations in 1957 under ICI Exports Limited. In 1962, ICI Paints was also incorporated to manufacture “Dulux” paints. In 1965, ICI Exports Limited changed its name to ICI Nigeria Limited and in 1968 it subsumed the paints company” (<http://www.capplc.com>).

The company specialises in the manufacture and distribution of wide range of architectural paints, protective coatings and auto paints. CAP Plc is a winner of the Nigerian Stock Exchange merit award (2006) and has retained the Pearl award for sector leadership in Chemical and Paints from 2004 to date.

Adedamola Olusunmade (a Maintenance Manager in CAP plc: Interviewed June 16, 2010).

Adedamola Olusunmade disclosed that:

- The implementation of predictive maintenance has produced significant impact on the company performance in terms of prevention of unexpected critical equipment breakdown and improving equipment effectiveness.
- The company presently implement a world class predictive maintenance program that involves online condition monitoring of some its critical equipment to ensure their reliability and availability for production.

Further investigation through semi-structured interview of operations and maintenance employees of the company revealed that:

- Management of the company are seriously committed to the implementation of effective predictive maintenance because they have adequate knowledge of the importance of the program to sustain the company performance and competitive edge in the industry.
- The company presently operates a *zero breakdown* maintenance policy.
- There is strong interest by the management to bring its maintenance personnel up to modern practice through regular training.
- The company only maintain a minimal inventory of machine spares.
- The company presently uses CMMS to plan, schedule and control its maintenance activities with adequate decision support system from the online monitoring companies.
- Accuracy of decisions resulting from present practice of predictive maintenance is high. There is little or no backlog of maintenance activities in the company's maintenance yard.
- The company currently have a reliability team that oversees the performance of its predictive maintenance program. This reliability team involves personnel from maintenance unit, production unit and external maintenance experts.

4.1.4 Case Study D: Rommy Poly-products Limited

Rommy limited was founded in 1999. The company specialises in the manufacture of polythene bag for both home and industrial use. The company has two production lines with critical equipment like extraction machines, air compressors etc.

Adekunle Segun (a Maintenance Manager in Rommy Poly-product limited: Interviewed June 17, 2010).

Adekunle Segun revealed that:

- The practice of predictive maintenance in the company is still limited to visual inspection, bearings lubrication and filter cleaning.
- The company is yet to experience any significant impact of the practice on its equipment availability and reliability.

Further investigation through semi-structured interview of operations and maintenance personnel of the company revealed that:

- The management of the company are not seriously committed to the implementation of predictive maintenance.
- There is a serious lack of knowledge on the part of the management of the company on the importance of predictive maintenance to the company performance and bottom lines.
- The company experiences regular breakdown of equipment. This rate is put at an average of five outages per week.
- The company has huge backlog of maintenance work as well as many machine scraps in its maintenance yard.
- The company maintains a huge inventory of spare parts to cope with the menace of incessant equipment breakdowns currently confronting it.
- The practice of predictive maintenance in the company does not involve the use of any condition monitoring systems. Furthermore, results of predictive maintenance program are not being presently used in scheduling and planning of maintenance work.

- The practice does not involve the use of any predictive maintenance tool such as vibration monitor etc.
- The company does not involve the use of operation routine data in making prediction or decisions on equipment.
- Most of the maintenance work is contracted out to maintenance contractors because of lack of knowledge and skill by the company maintenance technician in diagnosis of major equipment problems.
- The company has no plan to develop its maintenance personnel in implementation of proactive maintenance.

4.1.5 Case Study E: Poly-products Nigeria Limited

Poly-products Nigeria limited is one of the major players in the manufacturing of polyethylene products in Nigeria. The company was founded in 1962 and has three factories located in different parts of the country.

Engr. Okechukwu Nnamdi (a maintenance manager in Poly products: *Interviewed July 10, 2010*).

Engr. Okechukwu Nnamdi revealed that:

- The company still practices run-to failure maintenance strategy as the main maintenance strategy supplemented with practice of traditional predictive maintenance.
- There is no noticeable impact of the implementation of predictive maintenance on the company performance in terms of equipment availability and reliability.

Further investigation through semi-structured interview of operations and maintenance employees of the company revealed that:

- The company is currently bedevil by the incessant breakdown of its major equipment
- The company maintains a huge inventory of spare parts for its critical and/ or un-spared manufacturing equipment in order to cope with the incessant breakdown.
- There is little or no effort on the part of management to develop the knowledge and skill of its maintenance personnel in the practice of modern maintenance strategy.
- The management of the company are yet to see predictive maintenance as the panacea to the incessant breakdown of equipment. Rather, the management sees predictive maintenance as another cost centre.
- Maintenance cost still forms the major part of production cost in the day to day running of the manufacturing plant.

4.2 Comparison of case studies

This section provides the summary of differences and similarities observed among the case studies (*adapted from research findings presented in section 4.1*).

Case Findings	Case study A	Case study B	Case study C	Case study D	Case study E
Description of case study	Mouka Limited, a manufacturer of Polyurethane foam	Nigerite limited, a manufacturing of fibre cement roofing	CAP Limited, a manufacturer of paints and protective coatings	Rommy Poly-product, a manufacturer of polythene bags.	Poly products Limited, a manufacturer of polyethylene products.

Predictive Maintenance implementation	Implementation is still in development phase.	Practice is still rudimentary.	Employs a world class predictive maintenance program.	Practice limited to visual inspection, bearing lubrication and filter cleaning.	Practice is majorly reactive supplemented with traditional predictive maintenance.
Impact on Equipment Availability	No evidence of significant impact.	Impact is not significant.	Program has produced significant impact on overall equipment effectiveness.	Program yet to produce any significant impact.	Program has produced no noticeable impact.
Management Commitment	Management are not seriously committed to the program	Management are not seriously disposed to implementation.	Management are seriously committed to the program.	Management are not seriously committed to the program.	Management still see predictive maintenance as cost centre.
Condition Monitoring and decision support systems	Company does not use any condition monitoring tools.	Company is not considering procuring diagnostic or monitoring tools.	Company employs online condition monitoring.	Company does not employ any condition monitoring tools.	Company does not use any condition monitoring tools.
Frequency of breakdowns	Breakdown of equipment is still rampant	Intermittent breakdown of equipment is still rampant	Rarely experience breakdown of equipment.	Experiences regular breakdown of equipment.	Bedevil by incessant breakdown of critical equipment.
Maintenance Decisions	Operator routine data not used in maintenance decisions.	Accuracy of predictions from the present practice is poor.	Accuracy of predictions and decisions is high.	Accuracy of predictions and decisions from the present practice is poor.	Production input/ output variables are not used in evaluating equipment performance
Production	There is a lack	There is no	Personnel	Operator	Maintenance

personnel involvement	of link with production personnel.	synergy between production and maintenance.	from production involved in reliability team that oversees program.	routine data is not involved in maintenance predictions.	decisions are solely maintenance department responsibility.
Inventory of maintenance spare parts	Maintains a huge inventory of spare parts.	Maintains a huge inventory of machine spare parts.	Maintains a small inventory of machine spare parts.	Maintains a huge inventory of spare parts.	Maintains a huge inventory of machine spare parts.
Competences and Trainings	Management not committed to employee development	There is no conscious effort to improve personnel skills and knowledge.	Management strongly interested in developing maintenance personnel skills and knowledge.	Company has no plan to develop the skill or knowledge of its personnel.	There is little or no effort to develop the knowledge or skills of personnel.
Maintenance Management System	Maintenance Management system not used.	No tool or system in place to aid maintenance management.	CMMS used for maintenance management.	No system or tool to support maintenance management.	Does not involve the use of a maintenance management system.
Plant Capacity	Present productivity is far below average plant capacity of the plant.	The company is operating at less than 25% of its operating capacity.	The company productivity is within the optimal plant capacity and can be jerked up as needed.	The company Overall Equipment Efficiency is low.	The operating capacity is far below optimal capacity.

Table 4.1 Comparison of case studies

4.3 Correlation of Research Outcomes

The sections look at the status of different implementations of predictive maintenance programs presented in the case studies and try to determine what needs to be done to achieve an effective predictive maintenance program.

The results presented in the previous sections are obtained from reviewing of plant documents, maintenance process, and conducting interviews to determine the current predictive maintenance status in the companies in the case studies. The current status is then compared in section 4.2 to determine the company presently implementing a performing predictive maintenance practices. These comparisons identify areas that need improvement.

Furthermore, the effective practice covers all aspects of predictive maintenance including maintenance processes, technologies including automation, the management approach, work culture, and people skills and human performance.

The Figure below depicts present implementation of predictive maintenance in CAP Plc based on the research.

Figure below reveals the following critical findings:

- Top Management in CAP Plc is seriously committed to the implementation of predictive maintenance program. Management demonstrated its commitment also by adequately supporting training of employees on predictive maintenance implementation and by providing the necessary facilities for implementing condition monitoring. This has greatly improved the overall equipment effectiveness in the company.

- The research outcomes also affirm that CAP Plc has developed an effective predictive maintenance program through incorporation of an intelligent condition monitoring system. There is an effective production optimization and maintenance decisions which improve fault isolation and correction with great accuracy.

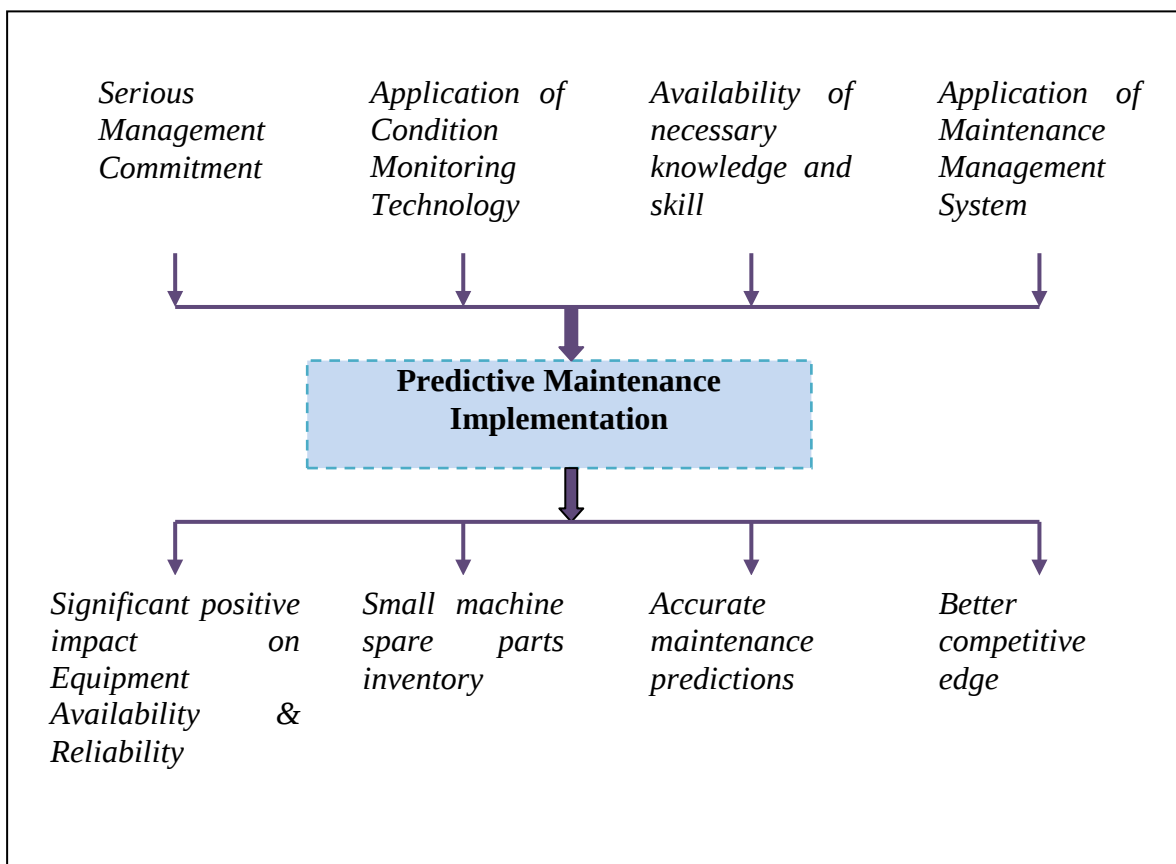


Figure 4.1 Predictive Maintenance Implementation in CAP Plc Limited.

From the figure above, it can be seen that the advantages of predictive maintenance are many. A well-orchestrated predictive maintenance will all but eliminate catastrophic equipment failures, minimize inventory and order parts and optimize the operation of equipment.

4.4 Implementation of a prototype system

This section provides insight to the result of implementation of a prototype model based fault diagnosis tool to enhance predictive maintenance at Rommy Poly-product Nigeria limited between August and September 2010.

The prototype system is developed for the centrifugal compressors health monitoring in the plant. The tool combines high-accuracy gas properties and thermal fluid compressor dynamics models to quickly and easily estimate the healthy state machinery behaviour under a given conditions. Machine behaviour performance can then be quickly compared to the healthy or predicted performance.

This *comparison* is used to generate a *residue* which is used to determine a deviation in the health or performance of the system. This step is generally referred to as *residual generation*. According to Mosterman J, Biswas G, and Manders E. (1999), “analysis of residuals in the context of the system model helps to generate one or more hypothesized root causes”.

When parameters deviate from their normal or expected values, the component associated with the parameter is considered to be faulty (Mosterman J, Biswas G, and Manders E., 1999). Hence different hypothesized faulty models based on varying parameters in the healthy models are generated through a process called *parameter estimation*.

According to Mosterman J, Biswas G, and Manders E (1999), “diagnosis of faults in engineering systems is the process of detecting anomalous system behaviour and isolating the cause of the deviant behaviour”. The authors pointed out that to

diagnose faults, the observed variable values and the system model can be employed to estimate parameters associated with the faulty system component.

Hypothesised fault models suggest modification to the normal system model which is employed to predict future system behaviour (Mosterman J, Biswas G, and Manders E., 1999). Continued monitoring and comparison of predicted behaviour of the hypothesised model with real process behaviour will be used to further refine the initial fault set. According to Mosterman J, Biswas G, and Manders E (1999), "it is unrealistic that system diagnosis can be completed in two snapshots. After measurement deviations are reported, the system needs to be tracked for a period of time till sufficient information from all other measurements becomes explicit."

Hence, faults whose predictions remain consistent with the process observation over time perhaps determine the root causes of the observed problems.

Several authors described that any process that involves monitoring, generation of hypothetical faults, prediction, and fault isolation with explicit system models as the core of the analysis scheme is referred to as model based diagnosis.

A detailed description of the experimental setup, equipment system modelling, and the programming algorithms involved in the construction and implementation of the prototype can be found in Annexure A. The mathematical equations involved in the development of the input-output model of the compressor are described in Annexure B.

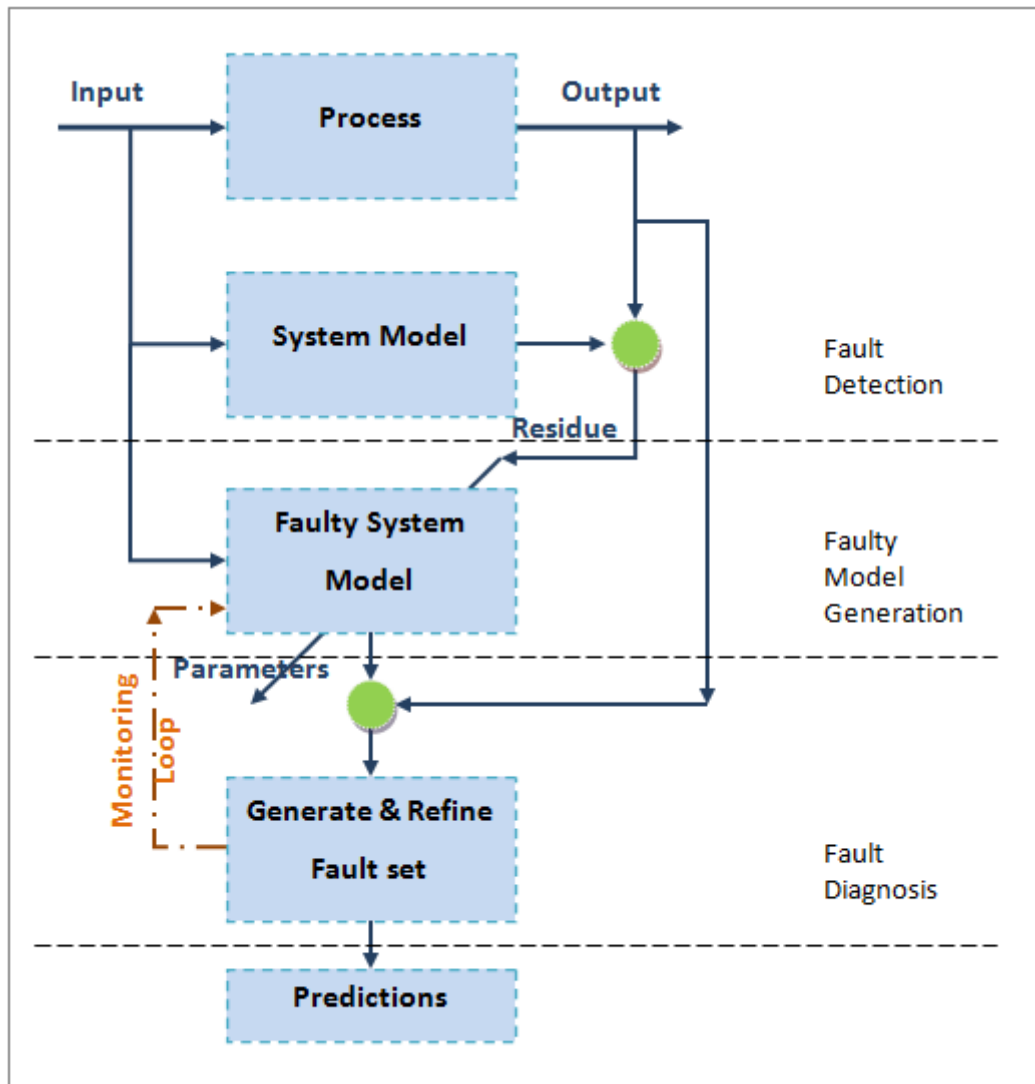


Figure 4.2 Model Based Diagnosis Reasoning (Akindele B, 2010)

4.4.1 Prototype Performance Assessment

To present a viable business case, the prototype system must have measurable and applicable metrics by which its performance can be assessed. One of the business drivers of the research is to improve the use of fault diagnosis tool to monitor system health in order to reduce unexpected outage or degradation in performance of the critical equipment through prompt fault detection and perhaps diagnosis.

Hence, reduction of unexpected outage after implementation can be considered a sound indicator. As unplanned downtime is reduced, the availability and/or the productivity of the asset should increase.

Furthermore, as the system aims to help plan and schedule maintenance work more efficiently and effectively using the model based health prediction technologies, it logically follows that the amount of unplanned maintenance should also decrease.

Lastly, the resources consumed through unplanned maintenance can also be used to provide an indicator of the success of the system. A direct comparison of these measures with pre-implementation values may however not reflect the actual performance, as the metrics rely heavily on various assumptions.

During the period of implementation of the prototype system, it was discovered that:

- The incessant outage of the plant due to failure of the air compressors in the plant was reduced to an average of less than three outages of the plant per week from an average of five outages of the plant per week.
- There was greater use of operation routine data in the daily predictive maintenance decisions on equipment.
- There was prompt and improved accuracy of resolution of equipment faults through proper identification of root causes.
- There was decreased backlog of maintenance work in the maintenance yard of the company.
- There was noticeable improved planning and scheduling of maintenance activities.

- There was increased awareness among maintenance and production personnel on the application of condition monitoring to aid maintenance effectiveness.
- There was increased interest in the part of management of the company in the procurement of a full featured condition monitoring tool to aid maintenance diagnostic and decision making.
- There was increased learning and performance by the maintenance technicians especially the junior technicians on troubleshooting and locating root causes of equipment failure.

Hence, the critical findings from the implementation of the prototype system include:

- Top management of the company as well as the workers showed great interest in applying the system as a condition monitoring tool.
- There is reduction in the unplanned outage of the air compressor system during the period of implementation of the prototype system in Rommy Ploy-product limited. Furthermore, decisions from the tool is used to plan and schedule maintenance work resulting in reduced maintenance backlog in the company.

4.5 Summary

Chapter 4 highlights the results and findings from the interview carried out in the five companies in the case studies.

The detailed results and findings of the research conducted including the analysis of the data and information gathered for this dissertation are presented in this chapter. Furthermore, the results and findings from the deployment of a prototype system to

monitor the health of the air compressors in Rommy Poly-product plant are also presented.

Lastly, while the results and findings from the interview are used to verify if there is need for the new framework; the results and findings from the deployment of a prototype system are used to validate the implement-ability and performance of the new framework as set out in section 1.3.

5. Discussion and Interpretation

Chapter 5 discusses the correlation of the findings of the research instruments, and also suggests a way forward.

5.0 DISCUSSION AND INTERPRETATION

The previous chapter presented the results and findings of the research. This chapter discusses the findings of the study and present the interpretations guided by relevant theories from the literatures, with respect to the data obtained.

A framework to easily implement a model based fault diagnosis system for condition monitoring for an existing predictive maintenance program is included in this chapter.

5.1 Analysis of Observations and Interviews

5.1.1 Predictive Maintenance Implementation: Management Approach

From the findings presented in *section 4.1*, comparisons between the implementation of predictive maintenance program adopted by five Nigerian manufacturing companies including CAP Plc are well highlighted.

Commitment of top management to the implementation of a predictive maintenance program in CAP Plc was very clear. This has led to the successful application of predictive maintenance through application of a condition monitoring technology. Equipment in CAP Plc have demonstrated a high level of availability, reliability and performance unlike equipment in the other Nigerian manufacturing companies who do apply condition monitoring technology in their predictive maintenance programs (*source: interviews*).

Adoption of a team (involving production personnel) for maintenance decision also led to an effective use of operation routine data in the condition monitoring of health/ performance of equipment through prompt fault detection and diagnosis in CAP Plc (*source: interviews*).

5.1.2 Predictive Maintenance Implementation: Application of Technology

Industrial plants search for powerful diagnostic and optimization tools to monitor and predict plant performance, issue early warnings for equipment diagnosis, sensor validation and predictive maintenance (Franke R, Antonie M, Babji B, Isaksson A, 2008).

Predictive maintenance program in CAP Plc involves the use of traditional predictive maintenance techniques enhanced with a computer based condition monitoring and decision support system (*source: interviews*).

Furthermore, the application of the condition monitoring tool allows increased use of operation routine data in continuous monitoring of health and performance of the equipment as a component of the overall plant. In the company, data gathering is semi continuous and does not wait till an undesired outcome/event is noticed.

This has led to prompt fault detection and diagnosis through holistic monitoring, trend analysis and decision support system. The accuracy of decisions from this intelligent decision support system is high and is evident in the high availability and performance of critical equipment in the company (*source: interviews*).

In addition, prompt fault detection through the condition monitoring tool also improves the maintenance planning and schedule practice in the company which is clearly evident in number of maintenance backlog as well as the size of equipment parts inventory in the company (*source: interviews*).

In contrast, predictive maintenance programs were mostly done routinely using only traditional predictive maintenance tools (e.g. vibration technology, thermography) in other manufacturing companies without cognizance of continuous condition monitoring. Data gathering and test of equipment begins only after an undesired performance/ event is observed. This has led to late detection of faults and sometimes serious degradation or catastrophic failure of the equipment before the undesirable event may be identified. Furthermore, many not easily detectable events normally lead to continuous unnoticeable degradation of equipment which normally culminate in the sudden breakdown of equipment in the four other manufacturing companies in the case study (*source: interviews*).

In the other companies in the case study, traditional techniques most times provide isolated view of the equipment fault (e.g. vibration only) and does not provide holistic data required for in-depth diagnosis and complete identification of root causes (*source: interviews*).

Many decisions based on the application of traditional predictive maintenance tools by maintenance personnel in the other Nigerian manufacturing are often based on instantaneous symptoms and depend on the level of knowledge and experience of the maintenance personnel involved. This also contributes to incessant downtime in the companies due to inaccurate and incomplete diagnosis of faults (*source: interviews*).

Conversely, evidence of huge equipment part inventory, maintenance backlog, and equipment scraps were discovered in other manufacturing companies. This further confirms the inadequacy of predictive maintenance decisions and/ or predictions

arising from application of traditional predictive maintenance tools without an intelligent condition analysis and decision support system (*source: interviews*).

5.1.3 Predictive Maintenance Implementation: Maintenance Process

Application of condition monitoring tool in CAP Plc helps in equipment health assessment and performance prediction which provides timely, relevant, and accurate information for effective planning and schedule of maintenance work. This further reduces the labour and time required for full diagnosis of equipment fault (*source: interviews*).

The decision support system helps in deciding and identifying the right maintenance work for a piece of equipment and provides an interface for integration with maintenance management system such as Computerised Maintenance Management System (CMMS).

Furthermore, apart from the use of analysis information from the condition monitoring system in maintenance decision support in CAP Plc, trending information are also used in continuous optimisation of process output and improvement of equipment performance (*source: interviews*).

5.1.4 Predictive Maintenance Implementation: Human Resources

The first hurdle to implementing an effective predictive maintenance program is having the right people; that is, staff with sufficient capacity, capability, competence and analytical abilities that is abreast with modern predictive maintenance practices.

The scenario at the maintenance department of the four Nigerian manufacturing companies, apart from CAP Plc, is not fully clear in this regard. The availability of

personnel does not present a major issue but rather disturbing, is the level of competence of both top and bottom level maintenance personnel in the modern practice of predictive maintenance.

These four Nigerian manufacturing companies do not have any form of programs in place for bringing its maintenance personnel up. Even though it is evident that training and skill development programs would produce excellent results by improving technical knowledge, increasing fault diagnosis skills and building a solid maintenance culture in the maintenance personnel. However, it is non-existent as a result of short sighted cost savings initiatives on the part of the companies' management.

Lastly, the use of traditional predictive maintenance techniques in the four companies, other than CAP Plc, only provides information on specific symptoms in equipment which are only relevant for maintenance decisions. Furthermore, the techniques are sometimes labour demanding and time consuming. It was discovered that a considerable effort is normally expended to make accurate and complete diagnosis decisions.

5.2 Analysis of Prototype Implementation

Section 4.4.1 outlines the findings of the implementation of a small scale prototype of a model based condition monitoring in Rommy Poly-product limited.

Following the implementation, management of the company show a serious interest in the application of condition monitoring technology (e.g. model based reasoning) to enhance their predictive maintenance program. The management also realise that

the use of a condition monitoring tool such as this is perhaps a solution for reducing the incessant breakdowns in the company.

This implementation also confirms the possibility of implementing a model based fault diagnosis in enhancing practice of predictive maintenance through continuous health assessment and performance predictions of equipment in Nigerian manufacturing companies. Also, this tool further confirms the applicability of model based reasoning for maintenance support in Nigerian manufacturing industry.

5.3 *Reducing Equipment Breakdowns*

To effectively tackle the issues culminating in incessant breakdown of equipment in the Nigerian manufacturing companies, included in this dissertation, a model based fault diagnosis framework is provided to aid in condition monitoring of equipment.

5.3.1 *The Model Based Fault Diagnosis Framework*

The **Model Based Fault Diagnosis Framework** (MBFDF) was developed to enhance the performance of predictive maintenance programs in Nigerian manufacturing industry by serving as a condition monitoring system for prompt automated fault detection and diagnosis.

The MBFDF also possess common features of Model based reasoning approach. Model based reasoning approach as presented in *section 2.4.2* is mainly concerned with the use of a model of a system or process to predict the behaviour of the system.

The MBFDF provides structure for implementing a cheap but effective condition monitoring tool for prompt fault detection and diagnosis in the Nigerian manufacturing companies.

More to the MBFDF is that its architecture will perhaps eliminate some of the problems (*highlighted in section 2.4.3*) associated with the use of model based approach for industrial applications especially the complexity in the generation and reuse of models.

Hence, this framework provides a coherent, consistent, and formal structure to capture function configuration-behaviour relations of a system as simple Input-Output mathematical model and facilitates reasoning about potential system faults from the model.

The detailed architecture of the proposed MBFDF framework is presented in Figure 5.1.

The framework in general has two processes, namely the model generation process and the model based reasoning process.

A. The Model Generation Process

This process defines the steps for generating the nominal process model used in the framework. The system model defines the relationship between system parameters, inputs (like pressure, temperature, flow conditions etc.) and the outputs. The process is as follows:

STEP 1

- IDENTIFY SYSTEM FUNCTION STRUCTURE AND FUNCTIONAL MODEL.

This step involves breaking the system or equipment down into possible logical function structure (FS) and functional model (FM).

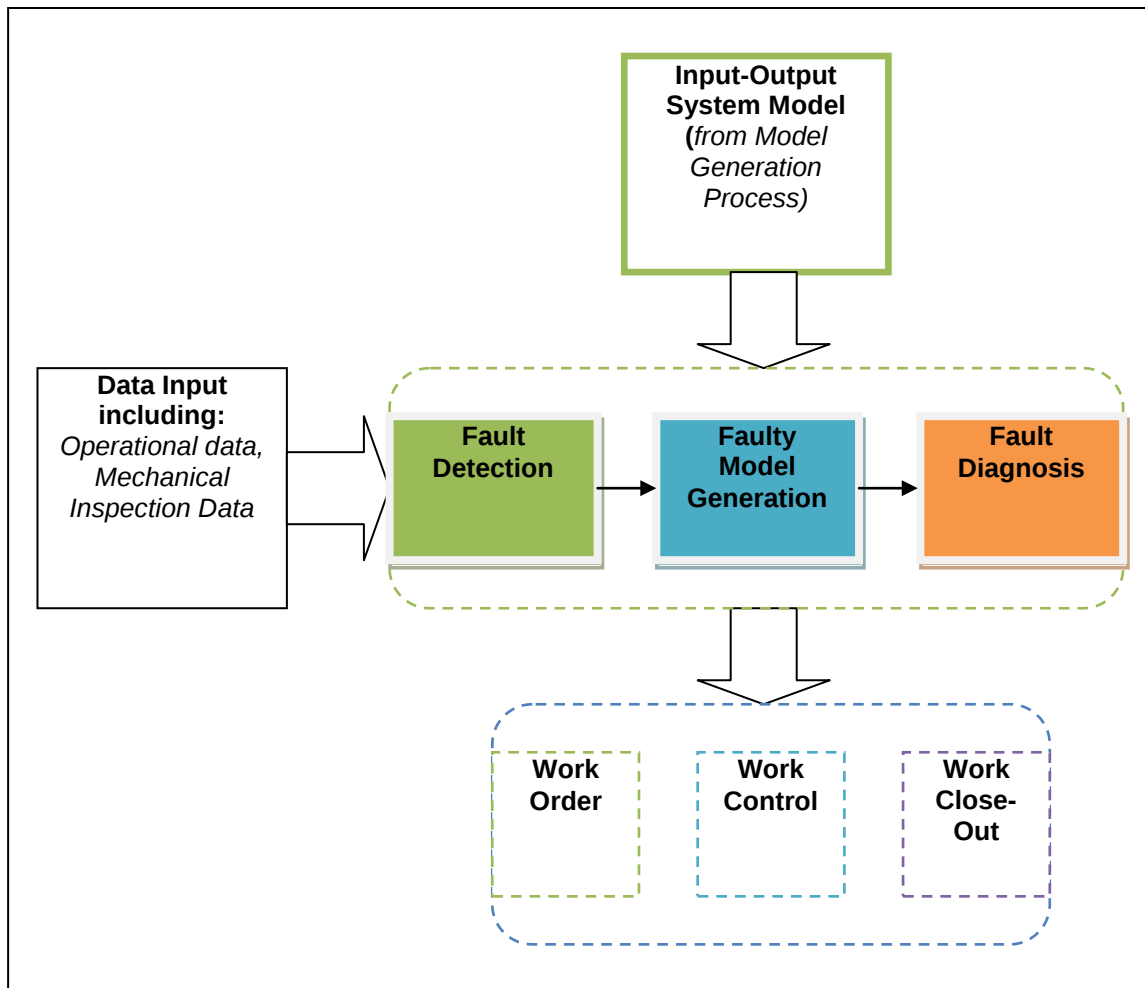


Figure 5.1 Architecture of the proposed MBFDF framework

“A function structure is a graphical, form-independent representation of a system that shows the decomposition of the overall system function into smaller, more fundamental sub-functions. The sub-functions are connected by energy, material, and signal flows that they operate on” (Kurtoglu T and Tumer I, 2008).

In this framework, a Configuration Flow Diagram (CFG) is preferred. A CFG strictly follows the functional topology of a system and maps the desired functionality into the component configuration domain. In a CFG, nodes of the graph represent system components, whereas arcs represent energy, material, or signal flows between them.

The component types in a CFG can be thought of as generic abstractions of common component concepts (e.g. valve, tank, junction, dc motor, battery, etc.). The CFG is a specific implementation of the topology or the configuration of a system.

“Overall, a functional model represents how input flows of a system are transformed into output flows. This approach to function-based modelling relies on verb-noun descriptions of elemental functions and a canonical list of flow types based on a standardized taxonomy called the Functional Basis” (Kurtoglu T and Tumer I, 2008).

The construction of a functional model and the corresponding CFG captures a direct mapping between the functional and the structural architecture of a system. “Capturing this mapping between functionality and component configuration of a system is crucial for accurately reasoning about failures at a functional level” (Kurtoglu T and Tumer I, 2008).

The task in this step may require the knowledge of an expert on the equipment as well as complex functional analysis.

STEP 2

- IDENTIFY VARIABLES ASSOCIATED WITH EACH FUNCTION MODEL

The first task is to define one or many outputs that are required from the model in order to achieve the objective of the task. The inputs are data and information that are required to produce those outputs.

STEP 3

- CATEGORISE THE VARIABLES

This step involves categorisation of the variable into the following:

- ✓ **Variable inputs:** quantities that are likely to change during the timeframe of the process. Some of the variable inputs will be decision variables.
- ✓ **Constants:** quantities that can be considered to be constant for the normal system behaviour. These generally represent fundamental principles of physics, chemistry, economics, geometry, etc. that govern the behaviour of the system. A deviation in the value of a constant signals a fault in the system.
- ✓ **Intermediate variables:** variables that have been introduced into the model to link inputs and outputs. The choice of intermediate variables is subjective, but, as long as the processing is accurate, the actual number of these variables is not critical, and it is always better practice to use more rather than less. This is because breaking down the processes into smaller steps makes the model generation easier to follow, easier to debug and overall reduces the need to use complex formulae, thus reducing possible sources for errors.
- ✓ **Outputs:** model outputs central to the objective of the task.

STEP 4

- DOCUMENT THE LOGIC FLOW

Link inputs and outputs using a series of user-defined intermediate or calculation variables. Document the flow of information between all the variables using a graphical representation method such as a bubble diagram or an influence diagram.

STEP 5

- **CREATE COMPONENT MODEL:**

Finally, the *behaviour* of the system is represented using a component oriented modelling approach. The approach involves the development of high-level, qualitative behaviour models of system components at nominal modes. System component models are derived from input-output relations and underlying first principles. Furthermore, the dynamic behaviour of the component in each mode is governed by a different set of physical laws and mathematical relations, and is therefore defined separately. This modular approach produces reusable component behaviour models.

STEP 6

- **CREATE FUNCTIONAL MODEL**

Accordingly, state variables critical to the system behaviour are incorporated into the representation by associating them with their respective CFG flows. The individual functional models describe the input-output relationships between these state variables in each component mode.

STEP 7

- **APPLY BASELINE DATA**

This step involves the use of baseline data such as manufacturer performance curve, field test data etc. to the input and output model equations to estimate any unknown parameter in the model equation.

STEP 8

- **FORM THE SYSTEM MODEL**

The last step involves combination of the component models into nominal system model as described in the CFG.

B. The Model Based Reasoning Process

This process involves the use of the nominal system model generated in the model generation process to predict the behaviour of the system in order to detect faults and obtain the possible root causes through diagnosis.

This process generally maps directly into the condition monitoring process in the effective predictive maintenance process chain presented in Chapter 2.2 and it involves three basic steps:

STEP 1

- **MODEL BASED FAULT DETECTION**

Model based Fault detection use the relationship between several measured variables to extract information on possible changes caused by faults.

A fault is defined as an unpermitted deviation of at least one characteristic property, called feature, from a usual condition. The feature can be any physical

quantity (e.g. *input*, *output*, *state variable* (time dependent function) or *parameter* (usually a constant) (Isermann R, 2004).

According to Isermann R (2006), the relationship between the measured input signal and output signal are represented by mathematical system model. Fault detection method then extract special features, like parameters, state variables or residuals. By comparing these observed features with their nominal values, applying methods of change detection, analytical fault sets may be generated.

“A straight forward way to detect system faults is to compare system behaviour with a system model describing the nominal, i.e. non-faulty behaviour. The difference of signal between the real system and the nominal model are expressed by *residuals*”. The design of residual can be made with transfer functions or in state-space formulation (Isermann R, 2006).

In this framework, to detect faults the observed variable values and the system model will be employed to estimate parameters associated with system components. When parameters deviate from their normal or expected values the component associated with the parameter is considered to be faulty.

Based on measured input signals and output signals, the detection methods generate residuals, parameter estimates or state estimates, which are called features. By comparison with the normal features, changes of features are detected, leading to analytical symptoms.

STEP 2

- **FAULTY MODEL GENERATION**

The goal of the preceding step is to generate several symptoms indicating the difference between nominal and faulty status. Based on different symptoms fault models are generated.

This step involves generation of several fault models to explain the deviation in the system behaviour. Normally, the process inputs and outputs are used to estimate various parameters in the input-output model equations. By assuming an unknown parameter for each parameter in the equation one after the other, a faulty value of each parameter is estimated. This estimated parameter value is then used to create the faulty model.

STEP 3

- **FAULT DIAGNOSIS**

Diagnosis of faults in engineering systems is the process of detecting anomalous system behaviour and then isolating the cause for the deviant behaviour (Isermann R, 2004).

The fault identification and isolation tasks require a model of normal operation of the system and a number of observable variables.

Measurement snapshots from the system determine the input and output values during system operation. Depending on the number of parameters a number of snapshots are required to solve for all the required parameters.

At times measurement value changes may remain within the specified margin of error for a period of time (Mosterman J, 1997) and therefore a deviating qualitative value is not observed for a number of steps. To avoid problems, tracking of behaviours due to faults using magnitude and slope changes are also employed.

The last step is to reach actionable conclusions based on the current deviation from established normal condition. Predictions/ decisions from this step can be useful for maintenance decisions, planning and scheduling as well as production optimization.

5.4 Summary

This chapter discussed the outcome of the findings of the research and also presented possible solutions to perceived problems of incessant outage of production equipment in the Nigerian manufacturing companies.

The next chapter will provide an overall outcome and conclusion of this dissertation.

6. Recommendations and Conclusions

An overall outcome of the dissertation, recommendations and conclusion, is presented in this chapter.

6.0 RECOMMENDATIONS AND CONCLUSIONS

The content of this chapter is derived from the significance of the results analysis and discussions of the research work carried out. Furthermore, a recommendation for future work is also presented.

6.1 *Conclusions*

This chapter presented a brief summary of the research dissertation. This dissertation identified problems associated with the implementation of predictive maintenance programs in the Nigerian manufacturing industry and established impact of current implementation of predictive maintenance on the availability of equipment in the Nigerian manufacturing industry.

Available literatures reveal elements that are vital for effective implementation of Predictive maintenance programs in the manufacturing industry. The results obtained from the empirical investigation conducted show the level of compliance and deviation of the manufacturing industry to the implementation of effective predictive maintenance program.

Based on the research findings, one of the case studies has adopted full-featured predictive maintenance practice and confirmed positive impact of effective implementation of predictive maintenance (*Section 3.5*). Some of the manufacturing companies found it difficult to successfully implement effective predictive maintenance program due to its complexity. They therefore only used the word 'predictive maintenance' in their maintenance practice without involving key elements that are vital to the implementation of predictive maintenance program.

Research findings sufficiently presented evidence to prove that a key element vital to effectiveness of predictive maintenance program is the application of condition monitoring system.

This vital element, if properly applied, have the potentials to revitalize predictive maintenance implementation and improve overall equipment effectiveness in Nigerian manufacturing company.

This dissertation presented a framework for combating incessant equipment downtime in the Nigerian manufacturing industry through application of model based fault diagnosis for condition monitoring.

The dissertation also present a model based prototype application to test the implementability and applicability of the frame work in a selected Nigerian manufacturing company.

Based on the analysis of research results and findings, it is evidence that the proposed frameworks can ensure effective implementation of predictive maintenance practice in the Nigerian manufacturing industry if carefully applied.

6.2 *Recommendations for implementation of the proposed Model Based Fault Diagnosis Framework for effective predictive maintenance*

Recommendations for implementing MBFDF as discussed in *chapter 5.3.1* of this dissertation are highlighted as follows:

- Management commitment is vital for the successful implementation of the MBFDF. Management should give adequate support to training of

personnel for effective implementation of modern predictive maintenance program.

- It is advisable that an integrated team (involving production and maintenance personnel) approach be adopted for implementing predictive maintenance program. Constituting the team should be based on expertise rather than status. Adopting integrated teams would enhance synergy between production and maintenance units thereby improving decisions making in terms of production optimization, maintenance planning and scheduling, and equipment inventory management.
- Computer support is vital for the successful implementation of the MBFDF. A computerized maintenance management system or a similar software for maintenance management should be adopted and set in place.
- Personnel should be assigned and be made responsible for setting up this framework. The various processes of the MBFDF should be handled by different experienced personnel, domain knowledge experts (in modelling, model based fault diagnosis and computer programming) for better performance.
- It is advisable that this framework be adopted for implementation by the Nigerian manufacturing industry to enhance the practice of predictive maintenance. This will evolve a manufacturing industry with less plant outage and better proactive maintenance practice.

6.3 Recommendations for further research

Production and maintenance departments cannot anymore wait for an equipment to fail to plan its operations. In today's businesses the maintenance function must allow

the prediction of anomalies in the production system and prevent any downtime (Deshayes L, Hjaiej A, Mihoc A, and Kouiss K, 2007).

Regular condition monitoring of machinery is key to predictive maintenance.

Condition monitoring is the process of monitoring a parameter of condition in machinery, such that a significant change is indicative of a developing failure.

The intelligent condition monitoring system offers many advantages as discussed in chapter 2. However, the Nigerian manufacturing industry has not been able to successfully apply the philosophy that underlies the application of such system in solving its industrial problems.

Further study that combines other intelligent fault diagnosis approach (e.g. expert system, fuzzy logic) with model based fault diagnosis approach for condition monitoring would provide a framework to supplement this research dissertation and enhance the positive impact of implementing full featured predictive maintenance on overall equipment effectiveness in terms of availability, reliability and performance of equipment in the Nigerian manufacturing industry.

6.4 *Limitations of the Study*

The major part of this research work can be said to be limited to the manufacturing industry in Nigeria. Not all data pertaining to this study can be documented for the companies in the case study because of the strict confidentiality tied to obtaining answers to certain questions while the some of the companies do not have in place a comprehensive maintenance record.

Furthermore, the slow response to interviews caused by bureaucracy and protocols in the Nigerian manufacturing environment may have prevented the presentation of a broader view.

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Annexure

Annexure A: Prototype Application

Experimental Deployment of a Prototype Application

As an effort to show the applicability of the model based diagnostic reasoning in manufacturing systems, a prototype application is considered in this section.

The application domain chosen for the model-based fault diagnosis paradigm envisioned here is comprised of the air compressors system in the Rommy Poly-product limited. Any deviation or failure in the air compressors system in the plant, usually result in a reduced performance or total outage of the entire manufacturing plant.

The air compressor system consists basically of an electric motor driven engine centrifugal air compressor. Albeit the specification of the air compressor as several functional components of different input-output behaviours differ significantly; however, the underlying aggregate functions remain the same. Thus, a collection of condition-indicators that are characteristic of anomalies in these functions provides a suitable platform for parameters monitoring.

The air compressor system is chosen because of its criticality in the plant. Figure 1 in Annexure B shows the input-output model of the air compressor system.

System Abstraction

According to VanDoren V. (2006), “a process model generally takes the form of mathematical equations that quantify the relationship between the process inputs and outputs”. The author explained that for more complex models are obtained through

more complex variables and more complex relationship. However, he noted that all models consist of four basic elements:

- *Input variables:* These are values that are used to predict the outputs.
- *Output variables:* These are the quantities that the model is designed to predict from the values of inputs.
- *Constants:* These generally represent fundamental principles of physics, chemistry, economics, geometry, etc. that govern the behaviour of the process. Their values do not vary over time as the inputs and outputs change.
- *Operators:* These define the mathematical manipulations required to compute the value of the outputs from the inputs and constants. They can be simple as the multiplication and division functions in equations or as complex as Laplace transforms and statistical distributions.

VanDoren V. (2006) further highlights that mathematical models can be useful for designing, implementing, testing and predicting systems behaviour in a virtual world.

The functional specification of the system is to maintain the net required air flow rate at a needed temperature and pressure for the cooling of products in the plant.

Basically, the air compressors' output performance is modelled. In this research, an input and output model describing the considered plant's equipment as combinations of functional components is used. Thus, a functional flow diagram is built up to explain the overall system response in terms of its component input and output variables (see Annexure B).

.Accurate mathematical analysis of the relations mentioned above requires the introduction of complex concepts of gas and thermal-fluid dynamics, as well as a good estimate of the physical parameters or constants involved in the models. Again, without going into such detail, a simple behavioural analysis offers a good understanding of the condition of the system.

Reasoning

In order to draw up the fault system model we need to enlist the components of the system that can go wrong.

The next step is the construction of the diagnostic decision engine. The diagnosis is actually done through the hypothesis generation sub-task, as follows. On one hand, we have the system whose behaviour can be observed, probably with a failure; on the other hand we have the healthy system model which is used to make predictions about the equipment behaviour. The models, typically describes the components of the system, their connections and their individual input-output behaviour. The difference between an observation and a prediction is called a discrepancy or residuals; the residual is used to detect a fault in the system.

The next step involves finding a match for the residual above in the faulty models.

Hench, residual obtained above is compared with residuals from implementation of different faulty states in the program to find a match. A match is called diagnosis. Both residuals and diagnosis are used to identify which parts of the device are possibly faulty.

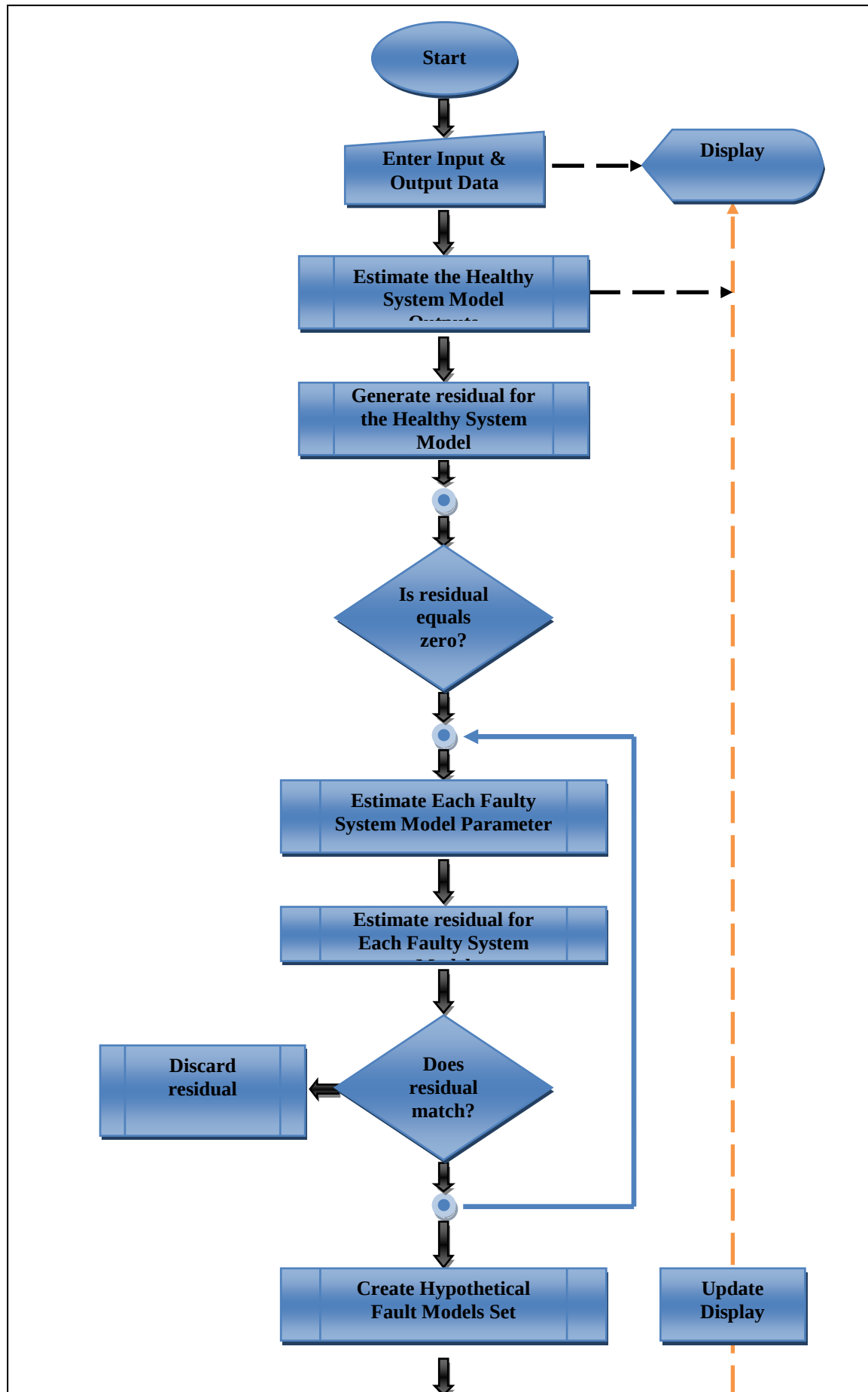
The algorithm for the engine is shown in Figure A. In this case, the structural and functional models of the air compressor system are given, and are, therefore, manually coded into a Visual Basic program. The system analysis and subsequent literature review to build the models of the air compressor are also done manually. The Model based fault diagnosis program takes over from this point to generate the rest of the diagnostic reasoning framework.

Model Verification

One of the most important steps of the model-based diagnostic reasoning methodology described thus far is the formulation of the input-output models. Consequently, it is vital to ensure that the generated model correctly captures the system behaviour we are interested in. “Model verification is the process of determining that a model implementation accurately represents the developer’s conceptual description and specifications” (Hughes W., 1997).

“Model checking is a technique for formally verifying finite-state concurrent systems. Specifications about the system are expressed as temporal logic formulas, and efficient symbolic algorithms are used to traverse the model defined by the system and check if the specification holds or not” (Bhaskar S., 2007).

A simple method used in this experimental prototype is to compare the model outputs with the equipment curve provided by the manufacturer as well as the system output under normal operating conditions. Annexure B provides a list of equations used for the input-output model of the compressor.



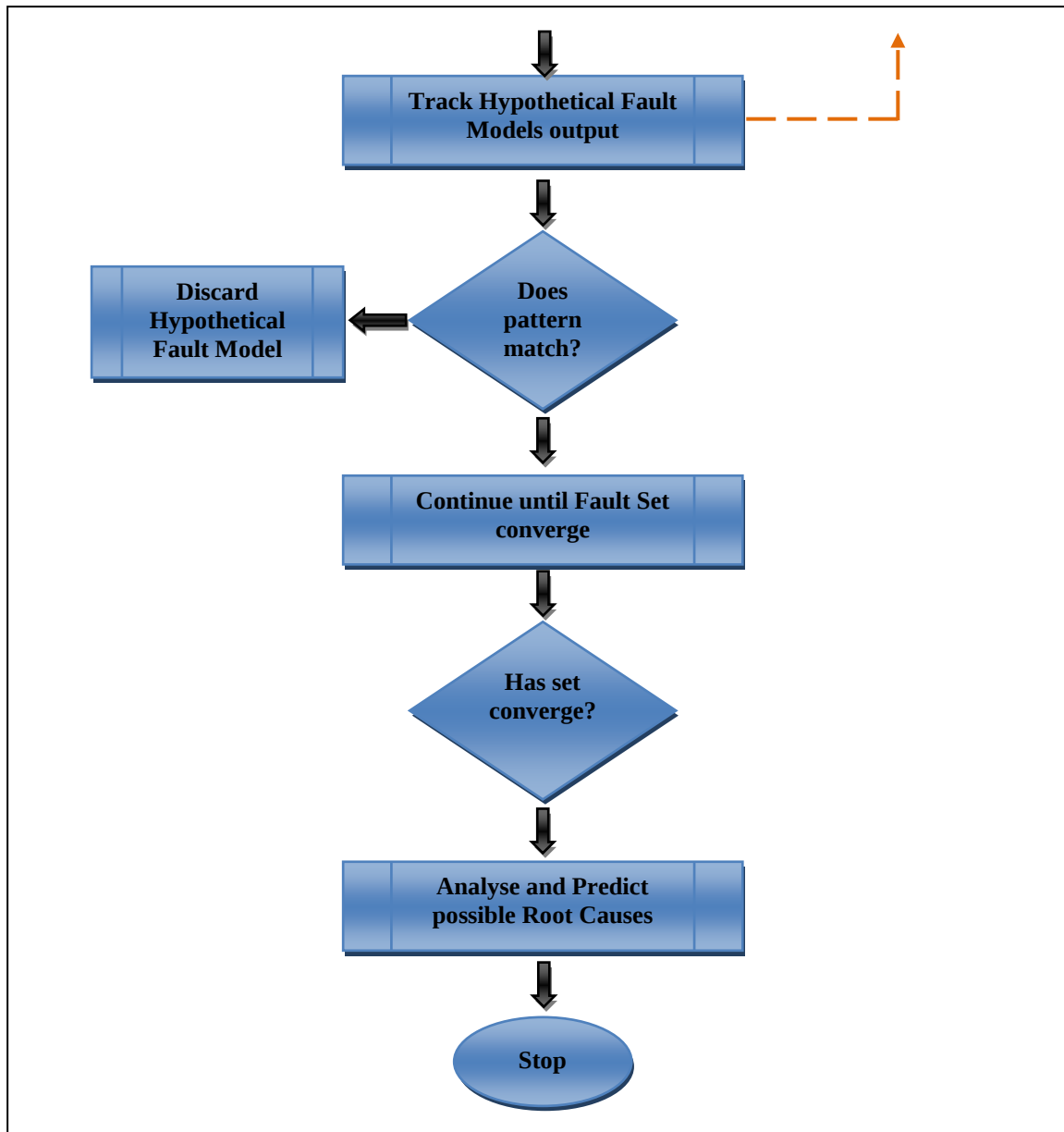


Figure A Algorithm for the Model Based Diagnostic Engine (*Akindele B, 2010*)

Annexure B: Prototype System Model

Compressor Input-Output Model

"A quantitative evaluation of compressor performance may lead to decisions that impact ongoing operations and/or maintenance. Without such an evaluation, decision makers tend to revert to time based maintenance decisions, or may not perform maintenance until a mechanical problem occurs, which may be long after the point at which repair becomes economically justified" (Chevron intranet, 2010).

According to the article, compressor and driver performance evaluations leading to prompt fault detection and diagnosis can support local operating and maintenance decisions in several ways. This includes improvements in energy efficiency, improvements to unit availability, identifying unit capacity range, and identifying the need for as well as timing of maintenance activities.

Performance degradation in centrifugal compressors may occur due to leakage around division wall, inter-stage, balance drum, or other internal sealing elements. Also, loss in performance may occur due to flow path degradation in impeller, diffuser, or return channel passages from corrosion, erosion, or fouling. In many company locations, compressor maintenance is not performed until a mechanical problem requires attention. Providing quantitative support for a decision to perform compressor internal inspection or maintenance based on performance is necessary, because the decision may involve a shift in local paradigms.

Head, Efficiency, and Power

This section briefly discusses how to properly discern important information and arrive at performance parameters that give a complete picture of how well the compressor is operating.

According to many manufacturers of compressor, head, efficiency, and power consumption are excellent indicators of how a centrifugal compressor is operating. Obtaining these variables as outputs of a system is a good idea of how well a machine is performing.

Five basic operating variables are needed for the head, efficiency and power calculations:

- suction and discharge pressures;
- suction and discharge temperatures; and
- inlet volume flow.

These measurements are usually available either on local gages. The compressor running speed must also be known, as it is needed later for comparison to the baseline curves that describe expected performance. The basic relationship in the input-output system model is depicted in the Figure below.

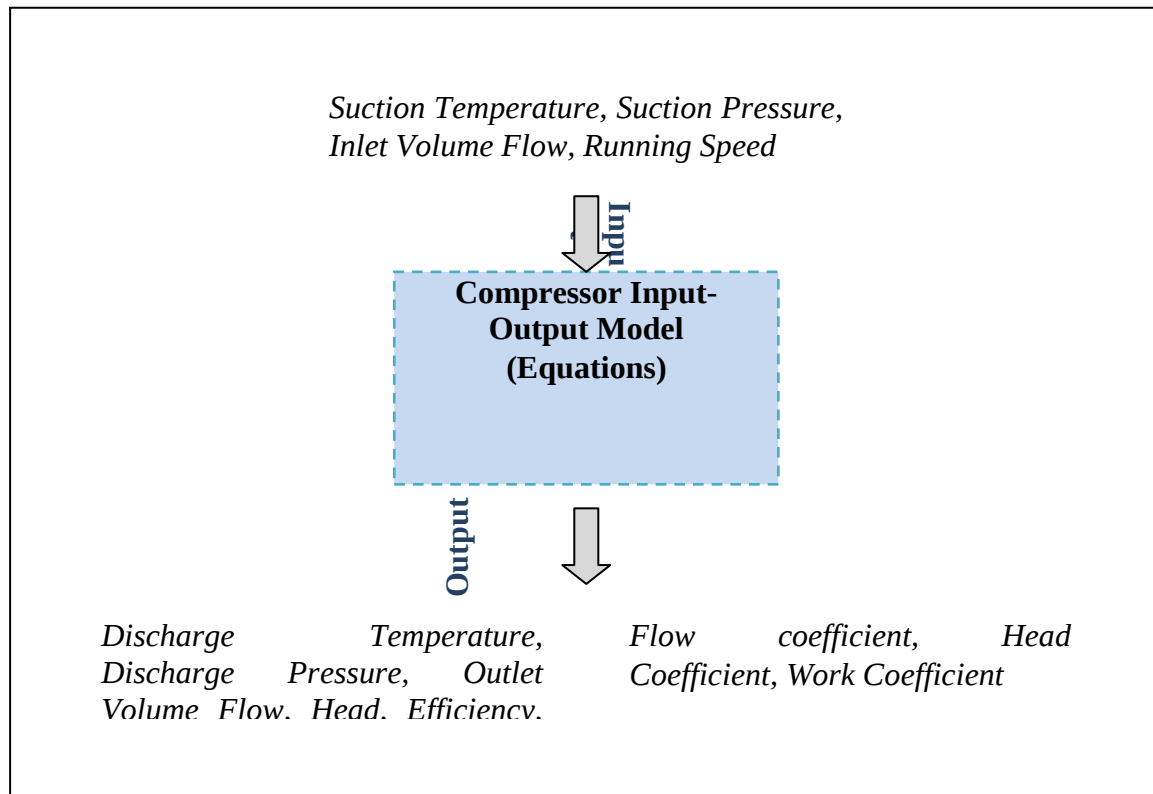


Figure B Input –Output Model of the Compressor System

Baseline Data

In the system model developed for the prototype application, baseline data is used to predict pressures, flows and speeds based on the mathematical model as well as the various input test data provided. These baseline data apart from being used to validate various input-output models developed for the compressor model, they are also used in this research to estimate various parameters that are not known in the system model.

The model in turn is used to estimate various output variables in the compressor. These variables are required to calculate the compressor head, efficiency, and power. These values are compared with estimations based on the real process output values to detect possible deviations in the system health or performance.

Useful Compressor Equations

The equations used in generating the input-output models for the compression are laid out below. Baseline data from manufacturer charts and test manuals are used to validate the relationships between the input and output parameters in the equations. The equations are in SI Units and are extracted from Chevron Intranet and are also verified from other literatures.

Useful Compressor Equations – S.I. Units

Polytropic Discharge Temperature:

$$T_2 = T_1 \cdot r^{\frac{n-1}{n}}$$

Polytropic Head:

$$H_p = R \cdot T_1 \cdot \left(\frac{n}{n-1}\right) \cdot Z_1 \cdot \left[r^{\frac{n-1}{n}} - 1\right] = \left(\frac{n}{n-1}\right) \cdot [(P_2 \cdot V_2) - (P_1 \cdot V_1)]$$

Pressure Ratio:

$$r = \frac{P_2}{P_1}$$

Specific Gas Constant:

$$R = \frac{R_o}{MW}$$

Polytropic Exponent:

$$n = \frac{\ln\left(\frac{P_2}{P_1}\right)}{\ln\left(\frac{V_1}{V_2}\right)}$$

Specific Volume at Pressure and Temperature (P & T):

$$V = \frac{Z \cdot R \cdot T}{P}$$

Polytropic Efficiency:

$$\eta_p = \frac{\frac{k-1}{k}}{\frac{n-1}{n}} = \frac{\frac{n}{n-1}}{\frac{k}{k-1}}$$

Ratio of Specific Heats:

$$k = \frac{c_p}{c_v}$$

Gas power:

$$\mathcal{P}_g = \frac{H_p \cdot \dot{m}}{\eta_p}$$

Mass Flow Rate:

$$\dot{m} = Q \cdot \rho$$

Gas Density at Pressure and Temperature (P & T):

$$\rho = \frac{P}{Z \cdot R \cdot T}$$

Percent Stability (against surge):

$$\% \text{ Stability} = \frac{Q_D - Q_S}{Q_D} \times 100$$

Impeller tip Speed:

$$U_2 = \frac{\pi \cdot D_2 \cdot N}{60}$$

Speed of Sound at Inlet:

$$a_1 = \sqrt{1000 \cdot Z_1 \cdot R \cdot k_1 \cdot T_1}$$

Flow Coefficient:

$$\phi = \frac{4}{\pi} \cdot \frac{Q}{U_2 \cdot D_2^2}$$

Polytropic Head Coefficient:

$$\mu = \frac{1000 \cdot H_p}{U_2^2}$$

Work Coefficient:

$$\tau = \frac{\mu}{\eta_p}$$

Inlet Relative Mach Number:

$$M_{rel} = \frac{W_1}{a_1}$$

Peripheral Mach Number:

$$M_{per} = \frac{U_2}{a_1}$$

Combustion Gas Turbine Efficiencies:

Mechanical Drive:

$$\eta_{th} = \frac{3600}{HR_{md}}$$

Generator Drive:

$$\eta_{th} = \frac{3600}{HR_{gn}}$$

Motor Power (3-phase):

$$\frac{\mathcal{P}_o = \sqrt{3} \cdot \eta_m \cdot E \cdot I \cdot PF}{1000}$$

Nomenclature – S.I. Units

a, a_1 = Speed of Sound $\left(\frac{m}{sec}\right)$

c_p = Specific Heat at Constant Pressure in $\frac{kJ}{kg \cdot ^\circ K}$

c_v = Specific Heat at Constant Volume in $\frac{kJ}{kg \cdot ^\circ K}$

D_2 = Impeller Diameter in m

E = Motor Line-Line Voltage in volts

h_i, h_d, h_s = Specific Enthalpy in $\frac{kJ}{kg}$

H_p = Polytropic Head in $\frac{kJ}{kg}$

HR_{md} = Heat Rate for Mech. Drive Gas Turbine in $\frac{kJ}{kW \cdot hr}$

HR_{gn} = Heat rate for Gen. Drive Gas Turbine in $\frac{kJ}{kW \cdot hr}$

I = Motor Current in amperes

k = Ratio of specific heats

$\dot{m}$ = Mass Flow Rate in $\frac{kg}{s}$

M_{rel} = Inlet Relative Mach Number

M_{per} = Peripheral Mach Number

MW = Gas Molecular Weight in $\frac{\text{kg}}{\text{kg mole}}$

n = Polytropic Exponent

N = Running Speed in rpm

P, P_1, P_2 = Pressure in kPa (abs)

PF = Motor Power Factor

$\mathcal{P}_g$ = Gas Power in kW

$\mathcal{P}_o$ = Motor Output Power in kW

Q = Actual Inlet Volume in $\frac{\text{m}^3}{\text{s}}$

Q_D = Rated Point Inlet Volume in $\frac{\text{m}^3}{\text{s}}$

Q_S = Surge Point Inlet Volume in $\frac{\text{m}^3}{\text{s}}$

r = Pressure ratio (ratio of absolute discharge pressure to absolute suction pressure)

R = Specific Gas Constant in $\frac{\text{kJ}}{\text{kg} \cdot \text{K}}$

R_o = Universal Gas Constant in $\frac{\text{kJ}}{\text{kg mol} \cdot \text{K}}$

T, T_1, T_2 = Temperature in K

U_2 = Impeller Tip Speed in $\frac{\text{m}}{\text{s}}$

V_1, V_2 = Specific Volume in $\frac{\text{m}^3}{\text{kg}}$

W_l = Relative Gas Velocity at the Inlet Shroud in $\left(\frac{\text{m}}{\text{s}}\right)$

Z, Z_1 = Compressibility Factor

η_{is} = Isentropic Efficiency

η_m = Motor Efficiency

η_p = Polytropic Efficiency

η_{th} = Thermal Efficiency

μ = Polytropic Head Coefficient

ρ, ρ_1 = Gas Density in $\frac{\text{kg}}{\text{m}^3}$

ϕ = Flow Coefficient

τ = Work Coefficient

Subscripts – S.I. Units

1 = Suction or Inlet

2 = Discharge or Outlet

d = Discharge

i = Intermediate

s = Suction

Constants – S.I. Units

R_o = Universal Gas Constant = $8.3143 \frac{\text{kJ}}{\text{kg mol} \cdot \text{K}}$