Application of Simulation Modelling to Machine Breakdown

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Abstract

Industrial technology has excelled profoundly in the past few decades, helping organisations throughout the world to be more efficient in all processes and keeping costs down. However, despite the abundance of several IT solutions, there exist many problems where more than one decision has to be made. Among the techniques supporting a multi-decisional context, simulations can undoubtedly play an important role as they provide what-if analysis and hence help to evaluate quantitative benefits. This thesis develops a simulation model for breakdown in an industrial machine, the main crusher in a cement factory. It also examines three important parameters (Drill Head, Dusting and Lubrication) of the crusher machine with the use of Bayesian network modelling which allows determination of suitable influencing factors in a precise and dynamic manner. The model also supports integration with management systems such as J.I.T, and MRPII. Witness simulation software has been used in this work to model the breakdown frequency of the Crusher machine and the associated parameters. The Bayesian Network Modelling is used to consider historical data and expert opinions; the Bayes' approach takes into consideration off all existing parameters that affect the machine breakdown directly or indirectly. This tool is capable of establishing a probability based on the information gathered about the parameters. The simulation model is developed further to enable the Bayesian Network Modelling to be applied via the Chain Rule to calculate the probability of failure. The findings of this research show the approach developed in this work, where the Bayesian probability development process is integrated into the simulation model. This provides a unique and dynamic tool to aid decision making in understanding machine breakdowns. The resulting simulator is a decision making tool capable of analysing the status of the machine and the associated influencing factors. This uses an approach based on multiple performance measures and a user-defined set of inputs based on historical and expert opinion. This work provides a methodology to study the importance of key parameters of the crusher machine. This in effect highlights the correlation between the governing parameters and the occurrence of breakdown.

Acknowledgments

The completion of this work would not have been possible without the many people who have in various forms provided support, guidance and inspiration. First I would express my appreciation and gratitude to my supervisor Dr. M. Latif. He has been very generous in his time and always a source of encouragement and inspiration to me. Also, I would like to thank, Dr A. Albarbar for his valuable support, the financial support and sponsorship by the Libyan government are highly acknowledged and appreciated.

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Last, but certainly not least, a huge thanks to the family and friends who have never complained when my PhD distracted me or made me late yet again. A special mention has to go to my mum, my father and my wife for their support and encouragement through all of my pursuits over the years.

Declaration

I hereby declare that this thesis is my own work and effort and that it has not been submitted anywhere for any award. Where other sources of information have been used, they have been acknowledged.

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Acronyms

SCM	Supply chain management
JIT	Just in time
MRPII	Material resource planning
TQM	Total quality management
SC	Supply Chain
DFD	Data Flow Diagram
WIP	Work In process
VSR	Variable statics Report
WCM	World Class Management
CPT	*Conditional probability table*
DAG	Directed Acyclic Graph
MTBF	Mean Time Between Failure
CF	crusher failure
BNs	Bayesian Networks
P	*Probability*
IMS	Intelligent maintenance systems

MRP Material Requirements planning

Chapter 1

Introduction

1.1 Introduction

Organisations invest huge amounts of capital on research and development that includes and investigates how to extract the optimum level of usage from the existing assets (i.e. machines and equipment). The simulation models developed as part of this work will demonstrate the novelty through the use of analytical software and tools that support one another i.e. Witness Simulation, Bayesian Network Modelling and Hugin Software. The use of expert experience and knowledge has been incorporated throughout the study, as it is vital when building useful models and helps build a greater understanding of machine breakdown.

The significance of an effective maintenance management program should not be underestimated, as its role is critical to the effectiveness of lean manufacturing. It is required to effectively reduce waste and run an efficient, continuous manufacturing operation. The cost of regular preventive maintenance is very small when it is compared to the cost of corrective maintenance in the event of a major breakdown, which interrupts production.

The reason of regular maintenance is to make sure that all equipment required for production is operating at the highest possible efficiency at all times Through short intelligent daily inspections, cleaning and lubricating, minor problems can be detected and corrected before they become or lead to a major problem that can require a production line to be shut down while corrective maintenance take place.

A good maintenance program requires the participation and support by everyone from the very top to the very bottom. An intelligent daily inspection enables informed decisions to be made as important information is gathered regarding different aspects of machinery. This information may include the general wear and tear of certain parts, problem/ disruption areas due to unknown reasons etc. The main idea behind this is to keep ahead of maintenance, by knowing where all the problem areas are, the easiest way to combat such issues and most importantly, to carrying out preventive work on a regular basis based on intelligent information to ensure breakdowns do not occur or at least keep them to a bare minimum.

For a very long time, maintenance related to machines has not been given the deserved importance and attention. These views have changed dramatically in the past two decades as industrial organisations strive very hard via the means of investment into research and development. Organisations understand, it is very important to get the best productivity from any and all equipment.

1.2 Aims of Research

The aim will enable the achievement of the hypotheses of the research. The hypothesis being the development of a new maintenance tool capable of tackling a variety of circumstances found in industry in relation to understanding machine breakdowns. This hypothesis must utilise historical data, available data and expert judgement using tools and techniques.

These aims of the research are to gather valuable data to find out the core reasons as to why breakdowns occur. This will identify problem areas in relation to the machine breakdown based on historical data and expert advice. Expert literature will be examined to consider previously used analytical tools to combat breakdowns. The analytical tools will be applied to the simulation model to develop novelty, ensure validity and contribution to knowledge. The overall aim of the research is to develop a simulation tool capable of aiding the maintenance strategy. The overall objective of this research is predominantly to understand and aid the reduction of breakdowns that occur on a machine, to develop such a tool that can be used by management to understand machine breakdowns at a superior level.

1.3 Objective of Research

The objective is to develop a suitable simulation tool for a manufacturing organisation enabling the provision of a framework to optimise the maintenance activities. The modelling technique used will be a combination of the Bayesian Network Modelling aided by the Hugin software. The two analytical tools will be implemented within the simulation model to develop a dynamic approach; the optimisation will provide insight into whether the breakdowns occur due to accurate reasons based on the parameters or are just simply based on the *Mean Time Between Failure*. The results of the optimisation will be to establish an accurate estimation of when breakdowns should actually occur, taking into consideration all influencing factors.

A key objective is to carry out a number of case studies in order to demonstrate the Bayesian Network Modelling and the supporting models. This objective is a very important aspect of the thesis as its purpose will be to demonstrate the integration of objective and subjective information into a maintenance model. The gathering of the objective information required as well as the elicitation of the subjective information will employ the supporting models. The information will be applied to the Bayesian Network Model and Witness Simulation Model in order to establish a maintenance strategy. This hypothesis must utilise historical data, available data and expert judgement using tools and techniques.

1.4 Structure of Thesis

This thesis is organised into ten chapters, each chapter was written to be self-contained and complete. To avoid excessive redundancy, lengthy information that is included in later stages of the thesis was occasionally referenced to an earlier section. The thesis comprises of the following chapters.

Chapter 1 Introduction

It outlines the introduction, aims and objectives of the study, novelty and contribution to knowledge with regards to using simulation as a tool to manage machine breakdowns. It describes the Libyan economy background with regards to the manufacture of cement and further problem areas.

Chapter 2 Specific Problems and Issues

This chapter draws attention to problems areas and related issues within the study in more detail to develop greater understanding and add value.

Chapter 3 Literature Review

The literature review develops a detail understanding of the analytical tools and software researched within the study to replicate existing machinery and problems. This chapter discusses of all the research literature taken into consideration in relation to simulation and maintenance problems. The use and the purpose of simulation in different industries is introduced, the application of the Bayesian Network Modelling in different industries and purposes is highlighted. This combined together develops a necessary background into simulation and tools used to combat machine breakdowns. The stochastic nature of the tools used within the study is also taken under consideration to enhance knowledge and highlight the effects thereof.

Chapter 4 Methodology for Research

This chapter highlights the methodology used in carrying out the necessary research required with relevance to machine breakdowns and the tools used to combat this problem. It presents the stochastic and discrete event programming solution to machine breakdowns via the use of integrated analytical tools. The solution provides a dynamic alternative with an in-depth reasoning behind the occurrence of breakdown. A number of different data capture methods are incorporated and the chapter finishes with the advantages and limitations of the methodology presented.

Chapter 5 Modelling the Problems

The modelling of the problems and the assumptions under which the model will be based upon are proposed with reasoning. It also presents the Witness simulation designer elements, their detail functionality related to the research, and the links between the models elements are explained.

Chapter 6 Modelled Systems

Chapter 6 presents the problem areas and developed model scenarios in further detail, it explains how the model is developed in a step by step process with reference to existing machinery and facilities, documenting the research undertaken and the data extracted. The machine parameters are modelled and combined to replicate the existing machinery using a discrete event system by Witness simulation software. Presentation is conducted with the use of a variety of visual aids and the logical programming commands and functions are explained in detail with reasoning.

Chapter 7 Data Collection, Validation and Verification

Chapter 7 highlights the data collection strategy used to gather all relevant data in order to investigate and develop greater understanding as how machine breakdowns occur and of machine breakdown models, using Witness simulation and further analytical tools. In- depth machine prognoses and specifications are introduced, while Validation and verification of all gathered data is done with the help of expert opinions, visual comparison of all results extracted from the model is highlighted with key performance indicators.

Chapter 8 Experimental Work / Analysis / Results

Chapter 8 discusses in detail all the experiments and results thereof from developed models. Full analysis is carried out on all results with relevant discourse and limitations with visual comparison of results.

Chapter 9 Discussion and Conclusion

Evaluates the study and discourses that helps bring together the conclusion of the research thesis.

Chapter 10 Further Work and Recommendation

This chapter presents further research that may be required and recommendation for future work.

References Section presents the references used in the study.

Appendices

A, B, C, D, E, F, G

1.5 Novelty and Contribution to Knowledge

The research aims to produce a new dynamic approach in strategizing machine breakdowns by enabling a “Predict and Prevent” approach, which can be used for the crusher machine in the cement manufacturing plant. This will guarantee a step forward towards an intelligent system as the gathering of data on a continuous basis is integral to the success in predicting and preventing the occurrence of breakdowns.

The application of the Bayesian Network Modelling and Hugin software within the Witness simulation model provides a dynamic system that can be used by the management to understand maintenance issues and machine breakdowns.

The analytical tools implemented within the simulation model have been previously used and proven to aid decision making by world leading organisations. The new model developed gives a dynamic approach and is a tool for management to help understand breakdowns and can be used to forecast future breakdowns based on the influencing factors and implemented analytical tools.

The novelty of the simulation model is the combining of existing tools to work together simultaneously on a dynamic platform rather than individually giving the results greater superiority. The automated response system within the simulation package helps bring to life the need for effective communication throughout all levels of the hierarchy as it alerts the management regarding existing parameters which can affect machine utilisation and in effect help not only understand but reduce breakdowns.

1.6 Background to Libyan Economy

The surge of globalisation has swept across all industries, and has accordingly provided numerous opportunities for those organisations who are well-established, namely automotive, cement, computers, textiles, and semiconductors. Prior to the globalisation surge however, [1], upon the expansion of experience into foreign markets. This subsequently helps to improve productivity and market share. The competition has now shifted from a previously national focus to one that is predominantly international. Furthermore, globalisation has ultimately meant that standards in terms of both performance and quality have been increased owing to the rise in competition. Therefore, a careful consideration will give a variety of fundamental elements, namely cost, dependability, flexibility, productivity, quality, service, and time compression. As a result, organisations are now acknowledging that there is a critical need to develop expertise on a global scale in order to be successful in terms of global markets.

In this new era of organisational growth, cement-producing organisations in Libya are in need of a varied economy with improved encouragement, promotion and support of the manufacturing industry. Accordingly, attempts steered towards updating the manufacturing industry especially in what is now a very competitive setting requires the further enhancement of additional knowledge, methods, procedures, processes, products, systems and tools in order to improve levels of productivity.

A summary of industrial-related development spanning from 1950 to 1980 reveals that neighbouring countries along the Northern coast of the Mediterranean, i.e. Italy, have shown significant development in a variety of critical industries, namely foods, leather and textiles. In contrast to other countries such as those located in the Southern Mediterranean in Libya has been significantly impacted, and has accordingly become a part of the development process [2]. Notably, this situation requires that the country's development is ensured. This may be achieved with the implementation of various tools, which are required in order to determine an approach which not only seeks to amend but also to dramatically improve the present situation in the country. Such progression would ultimately ensure Libya and countries like it would be in a good position to work in unison with the concept of sustainable development, which would, in turn, enable it to meet the requirements and standards stipulated on both a national and international level [3].

This would fundamentally assist in the following areas:

- Establishing an appropriate method for achieving sustainable industrial development;
- Establish new strategies, tools, techniques to enable production to increase;
- Establish a new rapport with global markets via the means of further education and training;

- Ensuring the transfer and promotion of more efficient, effective and environmentally friendly industries.

Libya can be described as a developing country; the country's main source of income is via its petroleum production, although there is a significantly important cement industry thriving within the country. Notably, it is stated that the cement industry is currently not effective in meeting the mounting construction demands both at a national and international level [3]. With this in mind, the country is currently dedicated to develop its overall manufacturing capacity with the aim of producing cement in a much more effective and efficient manner; it is believed that this would meet the requirements laid down by all markets, whether international or local, and would help to achieve the much sought-after status of World Class Manufacturing (WCM).

The World Report International states [4], various companies and plants within the industrial sector of Libya do not operate at their maximum capacity, potential, efficiency or effectiveness. It is further stated that such organisations commonly only reach 50% of their production potential being a core problem. With such statements taken into consideration, it can then be stated that organisations such as these are failing to utilise the opportunities they are currently provided with, and so there should be full advantages taken in order to make improvements.

A recent analysis of Libya, which was conducted under the supervision of the industry over view shows that Libya currently does not have an implementation of any form of strategic plan, which therefore highlights the requirement of improved industrial organisation management. Such improvements would lead to improvement growth for the country, and subsequent increased levels of competition on a global scale. [4, 5]

Importantly, it can be stated that in relation to the cement industry currently operating in Libya, there is the fundamental need to introduce technologies concerned with modern manufacturing management, in order to attain its full potential, and continue its operations in this way [5]. However, it is nevertheless the case that, at present, there are a number of operational barriers which are affecting the industry's ability to achieve full production. Such reasons include, for example, a lack of availability of spare parts, a shortage of skilled labour, and a lack of planned plant maintenance. However, various methodologies could be implemented in order to help to tackle such problems, namely Manufacturing Resources Planning (MRPII), Just in Time (JIT), Supply Chain management (SCM) and Total Quality Management (TQM). Notably, the actual implementation of these philosophies need greater adherence due to the lack of knowledge and imbedded cultural differences.

1.7 Challenges

A key complication in developing a maintenance tool to aid the methodology that can be utilised by an array of manufacturing industries, is developing a tool that can take into consideration the differing types of information, products and processes. All manufacturing companies will have gathered various information relating to times and costs of inspections, maintenance and repair activities, machine usage and breakdowns. The challenge faced in this study is the extracting of the most relevant information, from both objective and subjective sources, in order to produce an effective tool to aid maintenance methodology. The method of gathering data, the use of existing data and dependence on expert knowledge and opinions has shown to be a difficult process in terms of accuracy [6, 7, and 8]. The gathering of objective data in order to apply a modelling technique can be difficult as it generally requires many months or even years to attain sufficient data [7]. The use of subjective data gathered from expert knowledge can often come in a form which requires standardisation with existing data in order to establish a consistency of data ensuring confidence in the modelling results. The combining of both objective and subjective data requires elicitation in order to establish the data which is required to apply advanced modelling techniques to a manufacturing company.

1.8 Scope

The scope of this research is to develop an aid for the maintenance methodology, utilising an array of information from both objective and subjective sources. The purpose of the maintenance tool is to reduce the number of breakdown occurrences and gather extensive data with regards to the parameters enabling the reduction of costs associated with maintenance and inspection activities as well as prolonging the life of the industrial assets. This study must utilise historical data, available data and expert judgement using suitable tools and techniques.

Summary

Chapter 1 discusses the background of the study and in doing so highlights the inherent problems that exist in the Libyan industry today when using analytical tools in combating maintenance issues, notably machine breakdowns. The aims and objectives of the research study will serve to set out a logical structure of this thesis that is aimed at addressing the highlighted problems. The challenges the study faces in carrying out the research in order to achieve a unique novelty status within the study and the resulting development of a new management tool.

Chapter 2

Specific Problems and Issues

2.1 Introduction

This chapter presents the problems faced throughout the study, firstly, the gathering of all relevant data and the extraction of data as accurately as possible from both objective and subjective information. It highlights issues that are a faced on a daily basis from an industrial manufacturing perspective with regards to machinery in order to give an actual explanation as to why machines breakdown and to develop a deeper understanding. This chapter aims to describe the problems faced in more detail in order to develop a greater understanding from an objective and subjective point of view and revealing a balance between the two. All the research highlighted in this chapter has been extracted from the research report titled; Field Research of Cement Manufacturing [9].

2.2 Crusher Machine

The objective of this piece of industrial machinery is simply to crush the raw materials that have extracted from the quarry, to reduce the raw materials to a predetermined acceptable size ready to move forward to the next stage. This machine has 3 very importance parameters that have been highlighted throughout the study and as follows;

1. *Drill Head* – this is the primary tool of the crusher machine, it uses a high velocity industrial drill head that crushes the raw materials to a certain desirable size.

2. *Dusting* – the extraction of dust from the crusher machine is of key importance, as the drill head crushes materials, dust particles are prevalent and can reside in areas of the machine where a build-up can cause the machine to come to halt, for example, the drill head uses a hydraulic system that compresses against the raw materials, if too much dust gathers here, the hydraulic system that must constantly move up and down constantly can fail to move adequately.

3. *Lubrication* – the crusher machine has to be lubricated to ensure a smooth running of the drill to enable low levels of friction that is caused by the coming together of the raw materials and drill head. The lubricating of the hydraulics is also carried out, to aid the smoother running of the machine as a whole and enable the drill head to crush material appropriately.

2.3 Disregarded Parameters

Labour - workforce, people that help run the machinery have not been added to influencing factors due to the simple reason that, they are only involved in the repair and revamp of the machinery and hence have no direct influence on the running of the machine.

Faulty Materials - at times due to the nature of the manufacturing of cement, the load needed to be crushed by the crusher, can consist of inconsistent material due to be excavated from the quarry and the existence of huge rock formations.

Random Breakdowns - this is where a breakdown has occurred and no one has the knowledge as to why it has occurred.

2.4 Objective & Subjective Information

Quantitative data is measured or identified as numerical data that can be analysed using many different statistical methods and the results can be displayed using tables, charts etc. For example, in the form of a questionnaire, a researcher will ask a questions that include words such as how often, how many or percentage. This will give a numerical answer.

Qualitative data is used to describe different types of information; this is almost the opposite of quantitative, in which aspects/products are more precisely described data in terms of quantity and in which numerical values are used. Data originally obtained as qualitative information about individual items may give rise to quantitative data if they are summarised by means of counts.

Qualitative data described items in terms of quality or classification that may be 'informal' or may use relatively ill-defined characteristics such as warmth and flavor. Qualitative data can include well-defined aspects such as gender, nationality or commodity type. Qualitative data can be a pass-fail or yes-no indication again in the form of a questionnaire to form a numerical approach.

If qualitative data uses categories that are based on subjective ideas, then these are generally of less value to scientific research than quantitative data. It is also possible to obtain approximate quantitative information from qualitative data for example, asking a certain number of employees regarding their perception of the existing management and thereafter to rate it numerically.

In the case of machine breakdowns, both objective and subjective data exist, both consist of qualitative and quantitative information. The problem and solution is however to extract the best-suited information regardless of whether it be objective or subjective.

For example, the single machine under scrutiny (crusher) consist of three parameters, quantitative data is available as to how many times the machine has broken down within the past year or over any period. However, the reason for the occurrence of breakdown with reference to existing parameters is limited in terms of quantitative data, on the other hand, the existing management i.e. those in charge of the machinery who use it on a daily basis will have qualitative information with regards to the breakdown and parameters. The knowledge and experience of experts on fields are not available in quantitative terms; and hence this information has to be extracted subjectively.

Hence, the question of how one should assess the relative value of objective and subjective information is a significant problem area for researchers in all fields. A fine balance is required between these areas due to the nature of the research taking into account machine breakdowns according to the *Mean Time Between Failure* (MTBF). The majority of the subjective information disagrees with the MTBF approach as it seems far too simple when it comes to industrial machines; this approach simply divides the number of breakdowns by the time with no consideration for any other factors. A simple example of this based on the actual quantitative data extracted is as follows; the MTBF according to data is approximately 9500 minutes. This means the crusher machine breaks down every 7^{th} day; this result is inaccurate for industrial machines when compared to that of the existing management, expert knowledge and subjective data extracted. According to existing management and information from experts, machines have been known to breakdown a few times in a single week (due to parameter problems), however they also run continuously for several weeks without any breakdowns. Experts on the field hence disagree with the MTBF approach and shed light on new the development of new approaches that consider other and further related aspects a part from the time and number of breakdowns alone.

The simulation model is a good surrogate for actually experimenting with the machines and manufacturing management system, which is often very difficult to carry out and needs a lot of attention and time as well as not being cost-effective. Hence, it is of utmost importance for a simulation analyst to determine whether the simulation model is an accurate representation of the system under scrutiny, i.e., whether the model is represents true details. It is further, just as important for the model to be credible; otherwise, the results may never be used in the decision-making process due to lack of value, even if the model is valid.

The following are important techniques for deciding the appropriate level of model detail to reduce problems (one of the most difficult issues when modelling a complex system), for validating a simulation model, and for developing a model with high credibility:

- State the issues to be addressed and the performance measures for evaluating a system design at the beginning of the study.
- Collect information on the system and operating procedures based on conversations with the "expert" for each part of the system.
- Outline all information in these assumptions that becomes the major documentation for the model.
- Interact with the experts on the fields on a regular basis to make sure that the correct problem is being solved and to increase model credibility.
- Simulate the existing manufacturing system (if there is one) and compare model performance measures (e.g., throughput and average time in system) to the comparable measures from the actual system.

The most important problem that the study found is the occurrence of breakdowns and the need to reduce this in order to enable effective stability throughout the manufacturing process. In order to reduce breakdowns, a thorough investigation of the crusher machine and the existing parameters was paramount to the research. This became the key to both objective and subjective information, enabling the extraction of a balance of opinion from quantitative data and the qualitative data that happens to be the foundation of the simulation model developed in order to experiment and combat machine breakdowns based on all the available information mentioned above.

2.5 Summary

Chapter 2 explains the importance of the available information in terms of objective and subjective data, and the need for a balance to enable validity and credibility of developed model to combat breakdowns. Also discussed is the importance of conversing with experts in the fields in order to develop deeper understanding of the entire system and processes from a management point of view rather than a numerical approach. It highlights the purpose of the crusher machine and the existing parameters that have been taken under consideration and those that have not.

Chapter 3

Literature Review

3.1 Introduction

The research study incorporates many separate topics that are reviewed in order to thoroughly understand the problems faced and how to best combat the problem of machine breakdown. Many topics are interrelated. The findings in each topic can then be used to understand and recognise the problems that will be investigated with the help of expert knowledge.

The occurrences of machine breakdowns have a substantial impact on the entire system regardless of industry. While there is a substantial literature on modelling the time between breakdowns, duration of breakdowns and down times [10, 11, 12, and 13]. Very little literature takes into consideration the cause of breakdowns and the influencing factors therein. The lack of literature on this specific subject is evident in [15, 14 and 16]. It is also apparent even within the literature on the topic of modelling breakdowns there is very little discussion on the practical implementation of such models in real life [15 and 16]. Although many studies are carried out within this field, few are implemented due to the applicable changes that need to be made and more importantly, the practical aspects of implementation are not noted thoroughly due to the variation in time needed for implementation from start to finish [15 and 16].

This chapter gives an overview and discussion of the methods used in the available literature for modelling machine breakdowns and thereafter highlights the reasoning behind the chosen method used within this thesis.

3.2 Definition of a Machine Breakdown

Machine downtimes can be segregated into two types:

1. Deterministic downtimes are machine downtimes that can be scheduled, such as shift changes, breaks and planned maintenance [13].

2. Random downtimes are unscheduled machine downtimes: such as actual machine failures, broken tool changes, parts that require random attention [13 and 14].

3. A generalisation for a mechanism failing to perform its required function for an unknown reason when it was capable of doing so [16].

This thesis concentrates on initially the mean time between failures based on a numerical approach extracted from the research [9] and thereafter models the occurrence of random downtimes that takes into account influencing factors to reduce breakdowns.

3.3 Machine Breakdown Occurrences

There are many discourses about the randomness of machine breakdown occurrence. Binroth and Haboush [19] take into account and state that breakdowns are more time dependent as the occurrence of future events would depend to a certain degree on the times of past events. Bradford and Martin [20] also take into account that machine failure are not entirely random and scheduling the subsequent breakdown in simulation models may be dependent on the machines past breakdowns.

Venton [21] states that machine breakdown consists of mechanical failures that are often the result of physical wear and tear from everyday usage, and electronic failures that are concerned with chance. Hence, it is argued that electronic failures are arbitrary while mechanical failures should really be treated as time dependent failures.

This thesis firstly considers the modelling of a machine solely based on the times between breakdowns that have been extracted from the research [9]. A breakdown can be defined as a generalisation for a mechanism failing to perform its required function for an unknown reason when it was capable of doing so [16]. A breakdown is the event after a mechanism fails and before the machine is returned back to normal functioning order. The amount of time from the moment of failure to the moment of return is the length of the actual repair time [22, 23]. This period is also referred to as the repair time, time to repair and/or the machine downtime.

There are an array of different causes that may lead to a breakdown, machine operating times, maintenance conditions, parts replacements, machine wear and tear, design errors, operator skills and random machine failures [17]. It seems impossible to predict the occurrence of breakdowns due to the nature of all the possible factors that can lead to a breakdown [24, 25]. Thus, the machine breakdowns are considered to be random downtimes as chance plays a huge role.

Machine failures can be categorised by the time at which they occur, this separates machine failures into three types:

Early Life (Infant Mortality), the initial period of time where the failure rate starts very high gradually decreases, this type of failure is normally associated with faulty parts and inadequate use of machinery [26].

Useful Life, this period is usually the longest stable period of the part, and hence is also known as the intrinsic failure period or stable failure period. In this stage the failure rate is generally constant [26].

Wear out Life, this period is when parts start to approach the end of their life, where failures are predominantly caused by degradation and the failure rate increases dramatically with time, most of the time due to increase wear and tear [26].

These three aspects/portions of a part can be collated together and developed into a bath tub curve which is commonly used for electronic machines and can be seen in figure 3.1

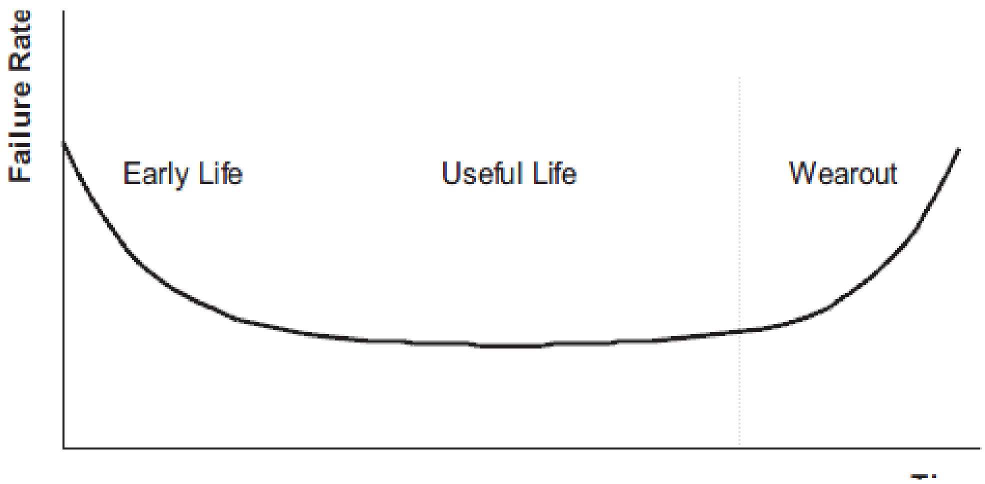

Figure 3 Bath Tub Curve for Machine Reliability [61]

There are many discussions, disagreements and developments regarding the true nature and the actual use of the bathtub curve [27, 28]. Condra [26] argues the correctness of the bathtub curve appears to be very subjective. Venton [21] on the other hand separates machine breakdown further into mechanical failures and electronic failures. It is suggested that mechanical failures are to be treated as time dependent as they are often a result of physical removal of material and electronic failures can be considered as random events as they are usually concerned with chance.

Porter and Finke [29] analysed machine breakdowns on integrated circuits and developed four categories:

1. Broken parts.
2. Time degradation.
3. Mechanical stress and serial effects of time degradation.
4. Mechanical abrasion.

Buzacott and Hanifin [30] identified two types:

1. Operation dependent cause: does not occur when the machine is in the idle state, happens after a certain number of operational cycles.
2. Time dependent cause: Can happen when the machine is idle; is due to some chance reason and happens after a certain period of time. The latter suggests that a breakdown can

occur even when the machine is not operating as well as being time dependent in the occurrences of breakdowns.

Ibe and Wein [31] theory is based on the duration of the failures. Law [32] gives a similar opinion about the two types of machine breakdowns.

1. Permanent failure: can be classed as inherent failure by industrial machine manufacturers, and requires the physical repair of a machine, which usually takes a long period to complete. It is referred to as major failure or corrective maintenance.
2. Intermittent failure: is classed as operational failure by industrial machine manufacturers, and can be taken care of by the machine operator and usually taking very little time to complete. This can be classed as a minor failure, preventive maintenance or condition based maintenance.

Blache and Shrivastava [33] term corrective maintenance as corrections that have to be undertaken to make a repair, indicating that there are more actions than just repairing the machine, from a failed state to an operating state. It is stated that the whole period of corrective maintenance can be separated into two main stages:

1. The active stage: The period needed to change the machine into a working state, i.e. actual repair time.

2. The delay stage: Waiting time caused by the absence of any resources, such as tools/parts or maintenance/ technical staff.

3.4 Modelling Breakdowns

The modelling of breakdowns in this thesis is based on a combination of the above occurrences of breakdowns. The model is based on a number of assumptions in order to function as accurately as possible to derive the best results. Binroth and Haboush [19] talk about breakdowns being time dependent due to the mechanical nature and the effects of previous work carried out. This aspect is addressed in the Bayesian model where all the influencing factors are taken into consideration. This approach can be classed as time dependent because the influencing factors of the machine are predominantly considered with time. As time passes, so does the life of existing parameters. The model indicates when changes and repairs need to be carried out based on the previous repairs. This highlights the points stated by Binroth and Haboush [19] where breakdowns are more time dependent as the occurrence of future events would depend to a certain degree on the times of past events. Bradford and Martin [20] also agree with this to a certain degree as they state machine failures are not entirely random. However, due to the number of reasons known and unknown, everyone agrees that at times failures do happen at random for unknown reasons regardless of machine or industry. This thesis firstly considers random breakdowns solely based on historical data [9], this model is called the mean time between failure model. This model is based on chance, but chance from historical data, which is then transferred into the mean time between failures. This transition one can argue simply depends on chance of failure as it is a time dependent approach. For example, based on the historical data [9], approximately 55 breakdowns occurred in a single year at random by chance. This does not mean that, breakdowns occurred every 6.5 days as indicated by the *mean time between failure*, but rather a few may have happen simultaneously in one week, which meant it was in working order for the next few weeks. On the other hand, the machine may have broken down a few times in a single day due faulty parts, there can be an array of different scenarios that resulted in the total number of failures. However, only the mean time between failures takes an acute numerical approach where the number of breakdowns is divided by the time, totally diminishing the reasoning behind randomness and chance occurrences of breakdown as the time between breakdowns remain the same throughout.

Venton [21] on the other hand segregates failures into mechanical and electrical, this thesis does not take into account any electrical aspects of machine failure but considers other parameters that will be highlighted later on. Venton [21] also clearly states that the mechanical failures of a machine are usually due to wear and tear. This is governed by the usage rate of the machine or part, indicating that, this does not fall under chance as it can be dependent on previous work and argues is thereby time dependent. This is similar to the approach taken for the Bayesian model, where all the influencing parameters are taken into consideration and as explained above are based on time, and hence are time dependent or usage rate dependent that is represented by time.

3.5 Modelling Assumptions

When applying the Bath Tub Curve (Fig 3-1) to the developed models i.e. ***Mean Time Between Failure*** model and ***Bayesian*** model, certain aspects need to be highlighted and are apparent. Firstly, the *Early Life* stage of the curve is not considered by either of the models. The *mean time between failure* model only considers the time between one failure to another, diminishing the chance of an early failure and the *Bayesian* model on the other hand is more or less time dependent. Therefore occurrence of a breakdown at the early stage is not possible and further, the Bayesian model is based on the assumptions that failures can only occur after a certain percentage of usage has been consumed by each parameter.

The *Useful Life* stage of the curve is considered by both models, but with certain restrictions. Due to these restrictions one can question the purpose of the curve in relation to the machine that is being modelled. As mentioned earlier on, the mean time between failure models, has (more or less) a starting point and a finishing point with no real randomness or chance, hence the entire curve can actually just be a straight horizontal line indicating the starting point and the actual finishing point. However, as the line comes slowly towards the end of its life cycle, this final phase can be categorised as the *Wear Out* stage. This has no real significance other than the indication of the occurrence of a breakdown, not chance of breakdown but rather a definite indication to a breakdown.

The Bayesian model's *Useful Life* stage, however, is one that fluctuates according to the existing parameters; it is not a horizontal stable line as the existing parameters must be seen as individual entities that combined together form the curve. However, if the individual parameter's bath tub curve is viewed, it will be similar to that of figure 3- 1, without the existence of the *Early Life* stage and no real fluctuation at the *Useful Life* stage, but the *Wear out* stage would be very real indicating the need for change.

As all three parameters have different life expectancies, the bath tub curve for each parameter will be of different sizes according to time, when this is combined together to form a single curve for the crusher machine. It results in the fluctuation of the *Useful Life* stage, and all three parameters reach towards the end of the *Wear* *out Life* stage simultaneously where the curve starts to increase vertically and carries on, this is where a breakdown may occur. The combination of all three parameters guarantees the chance occurrence where breakdowns are not only random but based on key influencing factors.

Condra [26] argues the correctness of the bathtub curve appears to be very subjective while on the other hand, Watson [27] Both are right in their own terms as the curves maybe based on or represent solely subjective information due to nature of the curve itself with no real fluctuation in between that should account for randomness. Watson [27] argues the curve can only be used for certain industrial parts that fall into the category of the three life stages i.e. parts that can evidently fail in the early stage due to product defects, and/or have a stable useful stage based on historical data after which the final stage being inevitable in all cases regardless of product/parts selection. Hence it is suitable for individual parts rather than a machine as a whole because the curve cannot is not used in such a manner that in takes into account all influencing factors and has total disregard for chance breakdowns within the useful stage of the curve.

This approach however has been applied to the Bayesian model with some leniency with the help of expert knowledge and both subjective and objective data extracted from the research undertaken. As highlighted, the early stage has been abolished, the <three parameters> are being considered on an individual basis that combined together acts as a single entity the crusher machine. The failure rate of this machine is based on all three parameters surpassing a 90% usage rate simultaneously [9], indicating all three parameters have to be around the critical stage of *Wear Out* in order for a breakdown to occur. This method has been applied under extensive dialogue with experts on the field that would agree to the above.

Similarly, other literature highlighted above suggests many different aspects of breakdowns, Porter and Finke [29] separated it into four, from which *Time Degradation* has been considered by both models. Buzacott and Hanifin [30] suggests two types from which only one type is considered by both models i.e. breakdowns can only occur at an operational state and not an idle state. The modelling of breakdowns is entire based on an operational state with no duration of any idle state.

Further literature such as, Ibe and Wein [31], Law [32], Blache and Shrivastava [33] indicate the need to classify failures into further segregated categories in terms of time i.e. the duration of time from the moment of failure to the point of start can be considered as the failure time. For example, from a technical point of view, only the time it takes for the technician to carry out the repair can be classed as the failure time. If for any reasons resources or parts needed to carry out the repair are not available, the additional delay will not be considered, so the time it takes for the arrival of parts has to be disregarded, all the different time slots in relation to entire repair process can be seen in Figure 3.2.

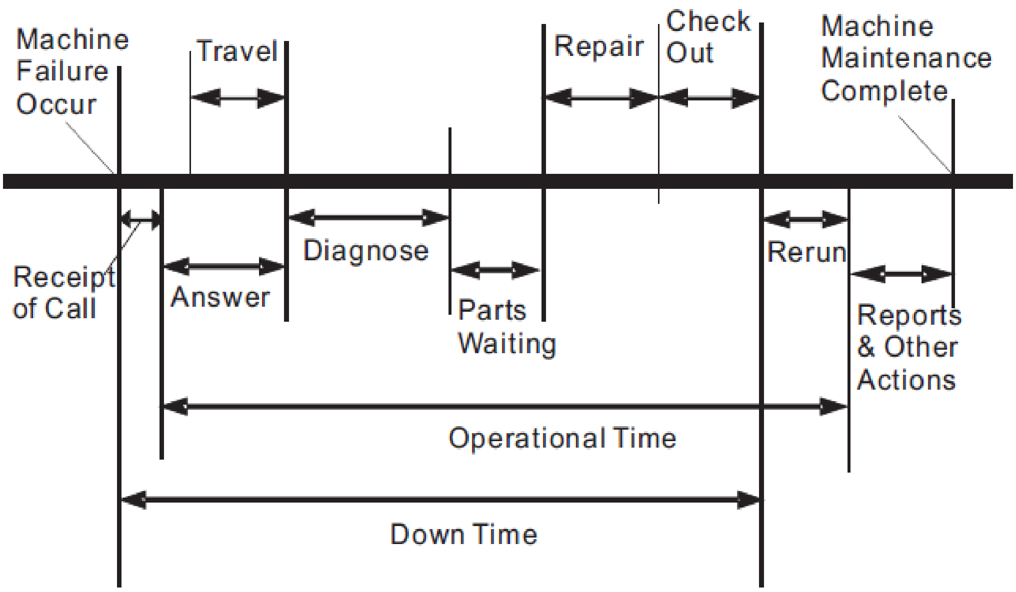

Figure 3 Segregation of time according to tasks related to repair

The models developed do not take into consideration-segregated times as shown in figure 3- 2 but rather base the model under the assumption that, parts are readily available, and resources are fully trained for the repair of any failure that may occur. Hence the models developed consider all the aspects shown in figure 3- 2 collated and as one single problem that takes an approximately time to complete.

3.6 Key Parameters of the Machine Breakdown

The time spent on collecting and analysing data can be vast and time consuming, many times it can also be very difficult to understand due to the different aspects within the study in terms of what they represent. It is even more difficult when the research is based around a subject area where no previous experience or knowledge is apparent or can't it be related to in anyway. Hence much research is required to attain a certain degree of understanding that includes both objective and subjective information in order to grasp hold of it in its entirety.

This study was made doubly difficult from the very start as the research of the existing facility and machine within had to be carried out on international soil. The research had to be done in Libya, where the first language happens is Arabic after which comes English which is only understood by very few All the research carried out that included historical evidence was available only in Arabic text, hence, the transfer of this historical data was also difficult due to language barrier i.e. when it comes to industrial aspects in relation to machines, parameters and maintenance, the technical vocabulary used for the identification of different aspects of maintenance is far greater than that of the norm.

One of the most crucial aspects of the research was the continuous dialogue with experts in the field. This helped develop a key understanding of all aspects as it allowed vast discussions to take place on an array of subject areas in relation to the study. All the discussion and communication revealed the very first point that was made i.e. the need to research why breakdowns actually occur according all the information available at hand and further discourses with experts in the field.

Therefore understanding the elements of breakdowns can really help with initial data analysis and understanding. The crusher machine has three key elements or influencing factors that affect the crusher machine directly. This is based on the historical data, current maintenance strategy/ duties within the field and expert opinions. The sole purpose of the crusher machine is to simply crush the extracted limestone from the quarry to a certain desirable size in order to move forward to the next stage. The three elements are as follows:

3.6.1 Dusting

This is a very important task for the maintenance team, and has to be carried out every 48 hours. The task includes the maintenance team using an industrial Vacuum cleaner which uses a very high voltage suction system. The vacuum cleaner has to be taken around the entire machine enabling it to remove all sand like dust particles from everywhere possible. This task has to be carried out because, as the machine progresses and crushes the raw limestone, small particles and fragments happen to find their way into many different places in and around the machine. The development of these particles can easily cause disruptions within the machine for a number of reasons. Hence according to historical data, the maintenance team make sure they carry out this task every 48 hours [9].

3.6.2 Lubrication

The crusher machine uses a hydraulic system that forces the *Drill Head* on to the raw limestone at a certain pressure enabling crushing to take place adequately. This hydraulic system enables a movement that oscillates up and down continuously and hence needs to remain lubricated in order to prevent the build-up of friction with intervening parts. Friction within the system can cause disruptions and deterioration of the standard of crushing and may even lead to the imbalance of pressure release affecting the *Drill Head*. Hence this tasks is carried out every 72 hours by the maintenance team, they apply a special industrial lubricate that has to be applied to many parts in relation to the hydraulics [9].

3.6.3 Drill Head

The element *Drill Head* is only a task for the maintenance team but actually requires a full team effort as it is a replacement of a key part. This element is the key to the entire system; it uses the directed pressure of the hydraulics to actually carry out the crushing by the use of friction and pressure combined. Its works on a rotating basis continuously grinding itself against the raw material, the *Drill Head* is made from a special metal to enable durability as it needs to carry out a very tough task. Due to the nature of the task, the *Drill Head* can only be used for a certain number of hours before it starts to deteriorate and decrease the standard of the crushed material. The replacement of the Drill Head has to be made every 7 days i.e. 168 hours of production time; else, the materials are not crushed to an adequate size and quality due to the deterioration caused [9].

3.7 Maintenance Overview

Industrial organisations recognise that having an effective maintenance management program is fundamental to the success of all manufacturing operations and keeping costs down to achieve world class lean manufacturing. Hence it is of interest to all industrial organisations to predict and prevent failures rather than fail and fix [34].

The significance of an effective maintenance management program should not be ignored as its role is very important in the effectiveness of lean and intelligent manufacturing. It is necessary to effectively reduce waste and run an efficient, continuous manufacturing operation, business, or service operation. The cost of regular maintenance i.e. preventive is very small when it is compared to the cost of a major breakdown i.e. corrective, at which time [35].

The reason of regular maintenance is to make sure that all equipment required for production is operating at the highest rate of efficiency at all times if not 100%. Through short intelligent daily inspections, cleaning, lubricating, and making minor adjustments, minor problems can be detected and corrected before they become a major problem that can shut down a production line due to breakdown where corrective action is required and production is lost.

A good maintenance program requires the participation and support by everyone from the very top to the very bottom [36]. The daily intelligent inspection enables intelligent decisions to be made as important information is gathered regarding different aspects of machinery i.e. the general wear and tear of certain parts or problem areas due to unknown reasons etc. The main idea behind this is to keep ahead of maintenance, by knowing where all the problem areas are, the easiest way to combat such issues and most importantly, and carrying out preventive work on a regular basis based on intelligent information to ensure breakdowns do not occur or at least keep them to a bare minimum. Steve Krar “Changing from a *FAIL and FIX* approach to a *PREDICT and PREVENT* approach” [34].

A true cost of machine breakdowns is very difficult to measure as the cost for a machine breakdown is more than just the maintenance labour and materials to make the repair. Actual costs equate too much more as many aspects have to be considered especially in industrial organisations and global economies, as organisations have very precise deadlines to meet. Where production has stopped due to breakdown of machinery or due to the availability of spare parts then targets are not being met in terms of production output results in deadlines not being met and further fines being incurred.

Maintenance has been viewed for a very long time as a dirty and boring job with no real significance; a job that did not add value to the productivity of the organisation and that was very narrow in terms of responsibility as management previously thought or did nothing about it other than wait for the technical staff to sort out the problem so they could proceed with the production.

3.7.1 Manufacturing Industry

This has changed dramatically in the past two decades as industrial organisations strive very hard via the means of investment into research and development and understand that it is very important to get the best productivity from any and all equipment as this adds essential value to the bottom line.

The simple question, "*Why do we need to maintain things regularly?*" The answer is, "*To keep things as reliable as possible*." However, the real question is, "*How much change or wear has occurred since the last round of maintenance*?" *Generally the answer is,* "*I do not know*" [37, 38]. This is the main reason behind intelligent maintenance, where it enables the gathering of information to make more effective informed decisions to enable efficient processing to follow.

Autonomous maintenance is very important [41, 42] as it develops operators to be able to take care of small maintenance jobs on the equipment they use on a daily basis due to using the equipment for such a long period of time, they may also understand certain protocols that will enable them to make effective decisions, further they as operators will take note of data regarding the machineries and be fully informed rather than a technical staff that may just simply look at the technicalities. Both operators and technical staff, as stated before, regardless of hierarchy need to work together to achieve the very best. This also falls hand in hand with philosophies such as Just-In-Time where the normal operators should receive increased responsibility [39, 40], training and education so they can take care of the equipment that they use and the skilled maintenance people can concentrate on technical repairs. This further helps to develop intelligent information as they spend the most amount of time with the designated machines or equipment [34].

With the era of technology at hand with advanced computing and information technologies, more equipment and machines are equipped with sensors on critical parts of machines to warn of potential failures before they occur so they can be corrected before they stop production. Integrated computerised systems are the core of intelligent maintenance as well as e-maintenance, where computerised systems aid development of management in order to make a more informed decision with regards to undertaking or being prepared to carry out maintenance at all levels.

Intelligent maintenance systems (IMS) *Predict and Forecast* equipment performance so that "Zero-Breakdown" status can be made a reality and not a possibility of the past [43, 44]. Zero downtime focuses on machine performance strategies to minimize failures. Data comes from sensors on equipment and machines and the information gathered by the organisation i.e. quality data, past history, failures, repairs and trending etc. Only looking at data from these sources (current and historical), it can predict future performance.

Industrial organisations today rely on sensor-driven management systems to provide alerts, alarms and indicators [43, 44]. Most factory downtime is caused by unexpected situations. There is no alert provided that looks at normal wear and tear over time. If it were possible to monitor the normal wear, then it would be possible to forecast upcoming situations and perform maintenance tasks before breakdown occurs hence the need of intelligent preventive maintenance.

Intelligent maintenance monitors equipment performance. If wear and tear starts to occur, there is enough time to carry out preventive maintenance on that particular area before failure. A machine can self-assess its health and trigger its own service request as needed and developed in this model. If this model works, then we will have a product that can manage its own service performance, and send out alerts regarding preventive and corrective maintenances before the actual failure. This will indicate ways to keep it running in a high-performance manner and most definitely result in lean manufacturing [43, 44].

However, many industries due to economies of scale, global economies and increased competition from throughout the world simply and only focus on the bottom line, the cost of downtime has a big impact on profitability. For example, if equipment starts to wear, machines may be producing parts with unacceptable quality and not know it for a long time. Eventually, machine wear will seriously affect not only productivity but also product quality.

World Class organisations have already taken a game-changing approach, implementing a new service business model to change maintenance systems into smart service and asset management solutions. They reduce downtime and provide the ability to look ahead at the quality of products before they ship by closely monitoring equipment performance and machine wear. Rather than reactive maintenance of "*Fail and Fix*" organisations are indeed moving towards an intelligent "*Predict and Prevent*" maintenance [34].

3.7.2 Maintenance Concepts

There are many maintenance concepts used and applied by industries worldwide, currently maintenance is a huge problem as it is combined with the availability of spare parts and other essential resources, warehouse stocks, the general tasks per machine etc. This is one of the main problem areas the manufacturing facility is facing, as many machines within the facility need preventive maintenance which is carried out with the use of spare parts and other necessary materials. Further, as parts are needed to carry out the necessary work, many times, materials are not available due to adequate stock control or unavailable technicians, this causes a backlog of maintenance work as parts and resources are not available. In order to combat these problems maintenance concepts are introduced to predominantly reduce costs by increasing productivity and reliability in machines and labour.

3.7.2.1 J.I.T

The core of JIT consists of the following three parts:

1) Flow
2) Flexibility
3) Developing the chain of supply

The contributors to flow in a cement factory include layout, material handling, cellular manufacturing and a focus on process balance. The production steps must be tied together. The layout must be linked, enabling final assembly, subassembly and component manufacturing steps to flow smoothly [40].

Flow is supported by flexibility, the time required to change over from the manufacture of one part to another must be kept to an absolute minimum, so that each production step can readily adapt to new orders [40, 41]. In the case of a cement manufacturer, the need to change is not necessary as they only produce one type of product that go through the exact same process every day of the year. The change-over time of a given production step must also be in balance with the other production steps to avoid bottlenecks. Many Japanese companies use flexible automation to support JIT as is used in the cement factory via the means of conveyors due to the nature of the products. Flexibility in the workforce (made possible by training the workforce to be multi-skilled) is of key importance and can only add to the core competences of the organisation [36, 37].

Having developed flow with flexibility in manufacture, the developing of the chain of supply is very important. This includes getting suppliers to deliver to the point of use, frequent delivery in small lots at precise times, and giving necessary data to suppliers to allow them to do so. Although the manufacture of cement in this factory includes supplying itself, there are many additional products that can be delivered as and when needed to the point of use.

At the manufacturer's end, this includes 'making today what is needed tomorrow', and rate-based production scheduling. Closely associated with this is the great attention paid to developing good forecasts and production plans.

All the above can be implemented into the simulation model to be verified e.g. the model enables the user to apply flow, flexibility and a sound supply chain. The model creates resources and activities exactly the way it is needed and eliminates the need for education, as the user creates the purpose of the operators etc.

- **Enabling of Just-In-Time (JIT)**

The striking aspect of JIT implementation by the Japanese companies is the extent to which the necessary preparatory steps are taken to enable JIT to occur. The following are the most important aspects as they are the enablers of JIT [37].

1. *Maintenance of plant and equipment* - This removes the need for buffering against machine breakdowns. In the Japanese companies, the routine maintenance tasks were tasked over to machine operators, which can be adhered to by the cement factory operators and the role of the maintenance function included maintenance planning, major repairs, training of machine operators, and ensuring that the new machines are properly installed and fully debugged. Thus, the implementation of productive maintenance and TPM is an enabler of JIT and should be implemented by the cement factory.

2. *Management of product and process quality* **-** Minimization of scrap, rejections and rework also removes the need for

buffering against poor product quality and quality losses. Quality assurance (the implementation of a quality system like ISO 9000, or QS 9000), statistical process control, and use of participatory approaches like 'kaizen' and quality circles are necessary pre-requisites and implementation of TQM is an enabler of JIT. All these quality assurance steps including J.I.T enable the organisation to becoming a WC organisation, to be able to compete in the harshest of markets and further out compete competitors due to its flexibility and system embedded within the organisation.

3. *Design of manufacturing process and selection of production equipment* **-** Although flexible automation is widely use, the selection of equipment should lay greater stress on having appropriate and properly used plant and equipment rather than going in for unnecessary and heavy automation. Instead of having special purpose machines, it may be better to use general purpose machines or many small machines. This will enable a high degree of routing flexibility. Moreover, the stress should be on developing flexible tooling and simplified set-ups. As technology increases faster and faster, new products for the manufacturing industries is inevitable, it is up to the organisation to calculate whether it is a viable proposition, especially in a cement industry where costs are very high and

the implementation of such huge machinery will disrupt or even stop production and hence be very time consuming. However, certain machines may well need replacing in order to keep up with competition, to enable faster production methods as well to decrease the amount of pollution.

4. *Development of people and training of the workforce* **-** The steps under this head include the following:

i) Development of teamwork

ii) Education, particularly of supervisors and also of operators,

iii) On-the-job training to develop appropriate levels of skill in the workforce,

IV) And Flexibility of work practices and development of flexibility in skills, through multi skilling.

The four aspects of development are of utmost importance regardless of organisation, industry, size etc, simply because it affects the organisation directly. The workforce is what makes the organisation what it is. No organisation in the world is successful because they have untrained staff, under skilled workforce, the non-existence of teamwork and have no education of what they are dealing with and hence their purpose at work. This development goes hand in hand with communication within the organisation; to be able to communicate affectively is a key to success. Within the cement plant, all the different departments need to understand the basic concept of internal suppliers and customers, whether it is from one department to another or one individual to another.

A necessary pre-requisite for these is a management which understands manufacturing systems and production methods.

5 *Design for manufacture and wide use of modular designs* - Design for manufacture and assembly reduces much of the uncertainties in manufacture, and the use of modular design enables the production of a large variety of finished products, while maintaining simplicity in manufacturing. These two together contribute to greater flow and flexibility in manufacture and at the same time maximizing responsiveness to customer needs.

6 *Provision of adequate technical support* – technical support that is qualified and knows exactly what they are doing, not only this but being efficient and carrying out the work as soon as possible to reduce the chance of bottle necks. With reference to the cement factory, they will have internal as well as external contract with organisations to handle expert jobs, these contracts have to be thorough and affective i.e. job is finished at the earliest and shortest time possible.

7 *Development of management controls* **-** Management controls are essential for minimization of machine breakdowns and quality losses in the form of faulty, scrap and rework.

As a philosophy, JIT's primary goal is the elimination of waste in the production system [36, 37 and 38]. Rework and scrap, and loss of production capacity due to machine breakdowns are very visible forms of waste and should quite obviously be eliminated. However, as a source of waste inventory is less obvious. The name just-in-time epitomizes the objective of minimizing inventory and this is done by getting the material to the next work centre, or (internal) customer, just in time for the next production step. This way the inventory build-up between production stages (work-in-process, or WIP, inventory) is minimized. Moreover, the JIT philosophy carries with it an objective of continuous improvement. The goal is to be getting better, and the way to measure a plant's performance is to see how little WIP inventory it requires for operating. Since inventory protects a plant in case of problems, in essence it hides the problems; so they go unnoticed, and unsolved. Problems must be found before they can be solved, and a sure way to find these problems is to reduce the WIP inventory.

The operating and organisational conditions of almost any firm are such that it is impossible for them to convert their operations management system to JIT in a single step. For large manufacturing firms, the size of the completely logistical chain is the main reason; it may be the lack of resources to be devoted to the implementation of JIT (human, financial and material resources). But beyond those reasons, several studies have shown that a successful JIT implementation is a complex process characterised by:

* An evolution of the organisational culture in place and a revision of the working methods and procedures.
* The implementation of new administrative procedures.
* The necessity of not perturbing or confusing the normal operations of the firm through poor human resources management.

Findings

From the very start the importance of maintenance is highlighted within the above philosophy indirectly although it may not use the word maintenance, the core being Flow, Flexibility and Developing the chain of supply. In order for any type of manufacture or production that uses machinery, maintenance is combined to the facets of total output and efficiency, maintenance allows the flow of materials, enables value to be added to products, flexibility and adequate requisite of supply to ensure fully working order to meet targets and produce appropriate output and quality. Further, the J.I.T philosophy recognises the needs and the trouble maintenance can cause in any industry and hence has maintenance as the first hurdle of enabling J.I.T. Affective maintenance abolishes many problem areas and backlogs that can result in huge deficits for organisation, especially in the cement industry.

3.7.2.2 **Materials Management**

The objective of materials management is to have the right material required for manufacturing, or production, in the right quantity, at the right location, and at the right time [39, 42 and 45]. This implies what is required, how much, and when of material requirements must be determined first. This is the basic objective of the materials planning and budgeting function. The questions that must be answered are the following:

1) Which material inputs must we get?

The inputs required are dependent on the outputs/end products planned to be manufactured/ produced.

2) The quantity of each of these inputs required based on availability in stores together with inventory on hand and or on order, the quantity of each of these should be ordered? The gross requirements of each of the required material inputs are calculated first and the net requirements are derived by subtracting from it the on hand and on order inventory.

3) When should the orders for each of the material be placed?

These decisions can be dependent on: where in the manufacturing process for the product are the particular material required and the lead times for manufacturing, namely procurement lead times for raw materials, or bought-out components and subassemblies, and in-house manufacturing lead times for the manufactured components.

Materials requirement planning (MRP) is a technique that converts the master production schedule for the end products into a detailed schedule for the raw materials and components used in producing the end products. The detailed schedule identifies each item required for all end products. It also determines when component parts must be ordered by the manufacturer and delivered by the supplier to meet the planned completion date for the end product. The underlying concepts for the techniques collected and unified by Orlicky under MRP in the early 1960's had been known for many years [46, 47], but they could not be fully exploited without the data processing power of modern computers today. Its early application was a bill of material explosion technique for determining the time-phased requirement of the components and subassemblies, and a method of releasing manufacturing and purchase order to the suppliers. Orlicky called the technique 'time-phased material requirements planning' [46, 47]. Before we take up the discussion the MRP technique, we must note the distinction between independent and dependent demand inventory item. This is necessary since this distinction is basic to the MRP technique.

- **Findings**

The objectives of materials management as described are of most importance to the facility, as this correlates to the three questions as to which, when and how much materials are required. These problem areas are solved via use of Witness Simulations automated response system aided by implicated equations. The systems notifies all management at all levels, regarding, how much materials have been used with regards to maintenance, how much materials are available and when new materials should be ordered from suppliers. The development of “what if” scenarios enable the user to see the types of problems that may arise by running time effective scenes i.e. the model developed can be run for any amount of time, this will show how much materials have been used with the number of maintenance carried out.

3.7.2.3 Dependent versus Independent Demand

Items stocked by a manufacturing company can be generally classified under following four headings:

1) Raw materials and purchased components.

2) Work-in-process.

3) End products and finished goods.

4) Maintenance items, spare parts and tooling inventory.

The first three kinds are directly related to the end products manufactured by the company. The fourth classed as inventory item, however, is not directly related to the end products and is to support the activities of in-house manufacturing. Demand for a given inventory item is termed *independent* when such demand is unrelated to the demand for other items, or when it is not a function of the demand of some other inventory items. The demand for spare parts and cutting tools is independent of the demand for raw materials, purchased components, or finished goods. Conversely, demand is defined as *dependent* when it is directly related to, or derives from the demand for another inventory item or end product [48, 49 and 50].

The first three inventory items are needed for the products; hence, we may call them as items of production inventory to distinguish them from maintenance and tooling inventory items.

The majority of the production inventory is in raw material, components and subassemblies which are largely subject to dependent demand. Their demand is derived from the demand of the end products for which they are needed. Dependent demand need not be forecast, as it can be precisely determined from the demand for those items which are its sole cause. On the other hand, the demands for the independent demand inventory items have to be forecast. Coming to the items of production inventory, the demand for the products, therefore, may have to be forecasted.

- **Findings_**

It is clear that inventory products related to the maintenance falls under independent demand as these materials are not directly related to the end product manufactured at the facility. However, further reading proves this matter to be dependent demand on the use or amount of materials that can be forecasted. For example, the facility plans to manufacture 1000 tonnes of cement, from this production schedule that will highlight the use of machinery, one can forecast the amount of preventive maintenance as well as corrective maintenance. Therefore, maintenance is both independent at times as well as dependent in other times.

- **Supply Chain Management (SCM)**

SCM (supply chain management) is often the cause of confusion, owing to the fact that there is a lack of clarity concerning whether it should be considered as a material management- or purchasing-related approach. Essentially, the definition of SCM makes reference to the overall process of planning, organising, and controlling the individual elements of the supply chain from materials through to manufacturing suppliers, etc.

a) **History of SCM**

SCM has existed for many years but was not until recent times identified as an organised form. The concept of supply chain management still existed from oldest trade system named barter system [51] when trade happened in exchanging of goods rather than money and developed later with the introduction of currency. Supply chain management was then recognizing by arranging the demand of one customer with the demand of other customers without any standardised approach. The first time a standardised approach was introduced was by Japanese after World War 2 in 1950’s.They not only introduced it, but also started its practices in a car manufacturing company named Toyota at that time they decide to keep SCM applications in their own country and also restrict it to transfers around the world. This is very useful technique to increase profits. Another concept of SCM was introduced worldwide in the early 1980’s.Then the big vendors decided to organise it by making more developments, it was unseen in progress till the mid of 1990 but since then, the growth of research in supply chain management has been rapid [52] engineers, prior to either purchase or modification (with the use of digital technology), therefore saving both money and time.

b) **Objectives of SCM**

Jacobs, FR [52] states that the concept of SCM has developed and progressed as a result of various business environment changes, particularly those which occurred during the last decade of the 20th Century. Importantly, in terms of defining SCM, it is stated that the ultimate concept is concerned with incorporating the various components of the supply chain into one flawless process. Essentially, this is not a simple task, however; this is owing to the fact that there are a number of different elements, all of which need to be taken into consideration. With that in mind, SCM should comprise goals which consider the follows elements of interest:

- The goals of individual firms.
- The goals associated with the integrated supply chain, such as the integration of all supply chain activities.

Simchi-Levi and Kaminsky [53] state that numerous factors have played a critical role in the increased levels of competition on a global scale. Examples include increasing consumer expectations and continuous technological developments. As a result, of such competitiveness, organisations are now experiencing increased levels of pressure in terms of improving customer service and decreasing costs [52, 53]. Notably they also reported that supply chain management can be defined as follows: ‘a set of approaches utilised to efficiently integrate suppliers, manufacturers, warehouses, and stores so that merchandise is produced and distributed at the right quantities, at the right locations, and at the right time, in order to minimise system-wide costs while satisfying service level requirements’. Essentially, such a definition is subject to various different interpretations in terms of its ideas, although the main concept is that supply chain management generally seeks to ensure cost-effectiveness throughout the implementation of its system and operations.

Notably, those actions which are undertaken with the aim of improving sales whilst minimising costs, as detailed in Figure 3-3, can be considered as sub-goals, which need to be achieved in order to achieve the ultimate objective, which is to improve overall consumer satisfaction, to improve quality, and to add value [54]. Furthermore, it is also noted that SCM is not only concerned with the reduction of costs, but also the general process associated with the improvement of customer and investor value.

Figure 3.3 shows supply chain management must be a core competency based on its impact on the bottom line. As indicated in figure 3-3, supply chain management affects two issues that dominate the bottom line, namely total costs and sales. The objective of supply chain management is therefore to maximise a business's profits by driving sales up and costs down [54 and 55].

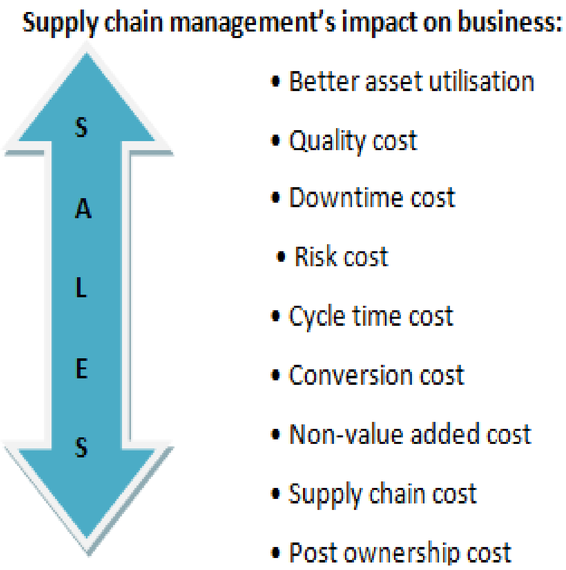

Figure 3 A graphic representation of supply chain management's impact [52]

3.8 General concepts of MRP and MRPII

Material Requirements planning (MRP) and Manufacturing Resource Planning (MRPII) are information integration business processes that are implemented using hardware as well as software applications that stores and delivers business data and information [56].

MRP is mostly concerned with manufacturing materials while MRPII is more concerned with the coordination of the entire manufacturing production from start to finish, which includes materials, finance, and human relations. The objective of MRPII is to provide consistent data to all management at all levels in the manufacturing process as the product moves through the production line accordingly [56, 57].

Paper-based systems and non-integrated computer systems that supply paper or disk outputs result in many different information errors, including missing data, redundant data, numerical errors that result from being incorrectly keyed into the system, incorrect calculations based on numerical errors. Therefore, resulting in unreliable data for the organisation can lead to very bad decisions being made by the management [58].

MRPII systems start with MRP, which allows for the input of sales forecasts, these forecasts determine the raw materials needed with reference to sales forecasts. MRP and MRPII systems depend on a master production schedule (MPS), the breakdown of specific plans for each product and its production line. MRP allows for the coordination of materials purchasing as MRPII facilitates the development of a detailed production schedule that accounts for machine and labour requisites and scheduling of the production is done according to the arrival of materials. MRPII output is a final labour and machine schedule. Data about the cost of production, machine time used, labour time and materials used, as well as final production numbers, is provided from the MRPII system to accounting and finance to develop an in-depth costing for management based on usage and production [56, 57].

Manufacturing resource planning (MRP II) can be defined as a method for the effective planning of all resources of a manufacturing organisation. Ideally, it addresses operational planning in units, financial planning in dollars, and has a simulation capability to answer "what-if" questions and extension of closed-loop MRP [56].

This is not exclusively a software function, but an extensive integration of people skills, dedication to data base accuracy, and computer resources. It can be a total company management concept for using human resources more productively.

3.8.1 Key functions and features

MRP II is not a proprietary software system and can thus take many forms. It is almost impossible to visualize an MRP II system that does not use a computer.

Almost every MRP II system is modular in construction. Characteristic basic modules in an MRP II system are:

- Master production schedule (MPS)
- Item master data (technical data)
- Bill of materials (BOM) (technical data)
- Production resources data (manufacturing technical data)
- Inventories and orders (inventory control)
- Purchasing management
- Material requirements planning (MRP)

- Shop floor control (SFC)
- Capacity planning or capacity requirements planning (CRP)
- Standard costing (cost control)
- Cost reporting / management (cost control)

Together with auxiliary systems such as:

- Business planning
- Lot traceability
- Contract management
- Tool management
- Engineering change control
- Configuration management
- Shop floor data collection
- Sales analysis and forecasting
- Finite capacity scheduling (FCS)

Other related systems such as:

- General ledger
- Accounts payable (purchase ledger)
- Accounts receivable (sales ledger)
- Sales order management
- Distribution requirements planning (DRP)
- Automated warehouse management
- Project management
- Technical records

- Estimating
- Computer-aided design/computer-aided manufacturing (CAD/CAM)

The MRP II system integrates these modules together so that they use common data and freely exchange information as and when needed, in a model of how a manufacturing enterprise should and can operate. The MRP II approach is therefore very different from the “point solution” approach, where individual systems are deployed to help a company plan, control or manage a specific activity. “ MRP II is by definition fully integrated or at least fully interfaced” [58].

3.8.2 Findings

The Material Management and Demand sections when combined together allow and cater for MRP and MRP11. These strategies have to work side by side in order to achieve strategic results.

MRP and MRP11 is more about the actual production of the product with little reference to maintenance as such, however, it is all about allocating the right resources, to the right place, at the right time, in the right quantity and staying ahead of schedule. None of this is achievable without the use of affective maintenance to the facility flowing forward with production schedules. The schedules highlighted only work well, when there are very few if not any disturbances within the facility. This strategy also makes aware the need to plan and control systems, it highlights the need to work with many other areas producing affective communication and using software as a strategy to move forwards.

The final paragraph where it states “MRP11 is by definition fully integrated or at least fully interfaced” is of great importance, this applies pressure on the importance of working as part of a team with affective communication and moving forward towards better systems i.e. software, to achieve total control [59].

The model developed, although for only a single machine demonstrates the ability to stay ahead of forecasts and problem areas by the use of a new computerised automated system that enables affective communication at all levels and extract key data.

3.9 Current Status of Maintenance Planning in the Manufacturing Industry

The manufacturing industries today exist in a very competitive market on a global scale. New technology has helped industries to prevail like never before and still improving to stay ahead of the global competitiveness, efficiency and keeping costs down is integral to success [60].

In today’s industry, to compete globally and be recognised as an outstanding organisation, organisations need to work that extra hard compared to the normal organisations. For example, an

ISO9000 is a certificate that can be acquired by following a set of guidelines; this aids efficiency, traceability and safety that are recognised by all industries and a must requisite by many countries. Many industry familiar certificate and achievements are available that enhance the performance of an organisation in the global market making it more attractive and even giving it that extra competitiveness. Manufacturing organisations strive for world class performance by adapting or developing the best strategy possible. The strategy normally involves a maintenance strategy or can be dependent on the maintenance strategy as the aim is to have maximum reliability of industrial assets by decreasing the number of possible breakdown occurrences [37, 38].

Maintenance strategy involves the collating of new data and the analysis of historical data, data collected is very important as it can renew knowledge that can bring about new ideas and develop solutions for known problems. This also helps in remaining and having that competitive edge in the global markets.

One of the major causes of increased costs incurred to organisations in terms of not meeting deadlines i.e. schedule delay, extended lead times for products and plant capacity is due to machines breaking down and causing backlogs and bottlenecks that in turn result in vast amounts of derelict labour and resources.

However, if an organisation can delay the point of breakdown or increase the reliability of machines i.e. extend the lifespan of industrial assets to its maximum length. This would increase efficiency and enable the gathering of knowledge so organisation can predict when a breakdown is most likely to occur and thereafter be ready for all the possible outcomes. Whether it is a machine breakdown, the changing of a certain part due to wear and tear, a general clean or lubricating of certain equipment or areas, the maintenance strategy will enable work to be carried out in an effective manner.

3.9.1 The need and justification for further research

The manufacturing industry has had a vast number of maintenance tools and techniques available for implementation for many decades now; with the advancement in technology, an array of software for their specific purposes in order to collect and manipulate data is also adequately available. This, enabling industrial organisations to move forward and establish a successful maintenance and inspection strategy where needed. However, a key problem is apparent i.e. there exist no single resolution to determining maintenance and inspection strategies for an organisation. The vast amount of different approaches that can be considered makes selection of the correct strategy for any organisation an overwhelming task.

Traditional maintenance and inspection tools and techniques can be very biased, relying on the views of maintenance personnel and management to establish inspection intervals. This practice often means that if breakdowns occur then inspections should be increased. Else, if no breakdowns occur, inspections could be reduced. The majority of maintenance and inspection analysis has come in combining one or more manufacturing philosophies to suite the specific needs of the organisation. New maintenance and inspection tools can also be very biased based on an objective point of view as all the data gathered is from historical data developed into statistical averages that can contradict expert knowledge and opinions. This approach normally means, according to the statistical anomalies, inspections should be carried out according to the data available from past events. This approach results in inspections being carried out at random intervals with no real significance to aspects other than time.

The challenge will still be to create a balance in extracting and using relevant information from both subjective and objective data. In order to develop a balanced approach, this thesis first uses the *Mean Time between Failure* derived from statistical averages of historical data. This forms the basis of the first model, where only objective data is used to predict the occurrence of breakdowns of the crusher machine without any attention to influencing factors.

Thereafter, the *Bayesian Network Modelling* is applied where statistical data of individual parameters are taken under consideration, with the use of subjective data from expert knowledge and opinion. This results in the discussion of credibility about which approach is best suited to predict breakdowns as both approaches are applied by the use of *Witness Simulation* that is validated by a stochastic approach.

3.10 An introduction to the modelling techniques

3.10.1 Mean Time between Failure

Data can be available in different formats from the maintenance department’s often not very detailed but rather simple numbers that represent the issue very vaguely, resulting in the information being often unusable. The majority of information gathered by maintenance departments is mostly general i.e. the name of the equipment or part number, time and date of the repair, the repairs made including spare parts used and the time the taken to return the equipment to production. Hence, the type of data collected is important as in may well consist of both subjective and objective information, along with some basic assumptions for the equipment or component investigated. The type of data required for the development of the *Mean Time Between Failure* is as follows:

- The available time.

- The operating time.
- Average downtime due to inspection.
- Average downtime for a breakdown repair.
- The number of breakdown occurrences.
- The failure rate

The *Mean Time Between Failure* has been extracted from the historical data available based on the number of breakdown occurrences that took place within the facility for the crusher machine over a period of 1 year dates. This data and approach is solely based on objective data gathered from the manufacturing facility [10].

3.10.2 Bayesian Network Modelling

Bayesian network modelling is a mathematical technique used to model uncertainty in a chosen area or a system, it can help identify and highlight links between variables [1]. The recognition of important variables as well as consideration of other influencing factors that seem to exist within the system is integral to the Bayesian approach. The Bayesian network modelling is a mathematical formula that calculates conditional and marginal probabilities of a random event at any given time [1].

Bayesian network modelling relies on Bayes' theorem as a rule of inference [3, 4], i. e. observations and data are used to update uncertainty of any parameter or node in a Bayesian model. This relates to the conditional and marginal probabilities of two random events, which calculates the posterior probabilities given observations of the two events. If events A and B are considered where event A is the influenced node and event B is the influencing node, Bayes' theorem states:

PAB= PBAP(A)P(B) **(3.)** **[62]**

Where:

P (A) is the prior or marginal probability of A.

P (A/B) is the conditional probability of A given B.

P (B/A) is the conditional probability of B given A.

P (B) is the prior or marginal probability of B.

This theorem forms the basis of Bayesian network modelling. A Bayesian network is a directed acyclic graph (DAG) that encodes a conditional probability distribution (CPD) at the nodes based on the arcs received. The nodes can represent any kind of variable or event. A Bayesian network is therefore a DAG encoded with a CPD, an arc goes from one node to another node making a connection in one direction only (acyclic). A node is generally drawn as an oval that represents the variable or event. The arc is generally a straight line with an arrowhead illustrating the direction from the source node, often called the parent node, to the other node (target), often called the child node, representing the probabilistic dependence between the two variables [3, 4].

1. Establishing relevant and accurate information
2. Establishing nodes with dependencies
3. Establishing of CPT (Conditional Probability Table)
4. Propagate Evidence
5. Model Validation

3.11 Witness Simulation

Simulation has much to offer to any organisation. The role of simulation is to evaluate alternatives that either support strategic initiatives or support better performance at operational and tactical levels. Simulation provides information needed to make these types of decisions. The simulation approach supports multiple analyses by allowing rapid changes to the models logic and data and is capable of handling large, complex systems such as manufacturing facility [10, 11, and 29].

Therefore, firstly a very good understanding of the organisation and its processes is required and thereafter very good knowledge of the model building software, which once combined, will enable effective and efficient results to be extracted [10, 11, and 29].

This software was selected due to its unique abilities to solve the business process and is generally quick and easy to explore solutions to many problems. Therefore, understanding of both the machine and the computer simulation package has been an ongoing process throughout the entire duration of the project [29].

3.12 Stochastic Analysis

Stochastic simulation can be used as a tool for predicting current or future reliability of machinery, it helps to understand machine failures by using confidence levels developed through replications and exploring the changes that occur.

The simulation model that has been constructed representing a crusher machine within a cement manufacturing plant can be trailed and tested stochastically. The crusher machine has three parameters; namely, drill head, dusting and lubrication. The consumption of these parameters results in the development of a probability of failure for the machine using the Baye’s theorem.

World class organisations invest vast amounts of capital into research and development to achieve a competitive edge over competitors. This competitive edge depending on industry can be on a number of different aspects [1]. For example, a new product, a new technology that helps the organisation reduce cost or even making certain business processes easier, new technology can mean the invention of a new product or feature etc. In the case of the cement manufacturing industry, to concentrate on how to increase capacity in order to cater for current and future predicted demand [2, 3]. Their research and development may include the consideration of machinery, the type of machinery, new machinery or new systems that enable a prolonged usage of machinery.

Often planned changes result in the implementation of new strategies or philosophies that enhance productivity via the means of quality maintenance management. Maintenance of machinery is integral to all industries in order to maintain lead times and produce consistent quality products that are free from faults. [4].

Hence, the ability to be able to predict the future reliability of machinery is pursued and encouraged by all industrial organisations in order to reach world class status i.e. to move from a '*fail and fix'* approach to a '*predict and prevent*' approach.

The development of the stochastic model is really an attempt to fine tune the results extracted, because stochastic analysis is based on numbers generated randomly. The results that are extracted i.e. failure probability, should be different for every replication made, every replication will use different number streams and hence there should be a variance in the probability of failure for each replication. This will help to understand the strength of the results and further enhance the validity.

3.13 Summary

This chapter has presented an in-depth overview of breakdowns and a general overview of the maintenance concepts. The manufacturing industry has been highlighted in general and the current status of maintenance planning has also been evaluated. These aspects combined together form the need and justification of research into why machines breakdown and how they can be reduced using certain techniques. A methodology has been developed where, the *Mean Time Between Failure* approach and the *Bayesian Network Modelling* has been used acting as the basis for the model developed using Witness Simulation. Thereafter the model is approached from a stochastic nature enabling enhanced results to be extracted and enabling greater understanding.

Chapter 4

Research Methodology

4.1 Introduction

The key obstacle in the development of a *Witness* simulation model is the collating of the available information and extraction of that which is closest to the true to life system. Research into many different areas of the machine including existing parameters was required before the actual development of the model could be started. Once the adequate amount of data was in hand with regards to the machine and parameters, development could start and move forward with the help of expert knowledge. Development and research had to be carried forward simultaneously on a continuous ongoing process to ensure the model was realistic, this was further aided by the help of experts in the field.

Analysis will be carried out to show the implications of the *Mean Time Between Failure* technique in the research undertaken after which the *Bayesian Network Modelling* was applied for a comparison and to increase clarity with reference to the research data collated. To enhance the system and further understand the results, a stochastic approach was used as making it as a whole a viable tool for management with the help of expert knowledge.

4.2 Research Focus

Witness simulation was chosen due to its high flexibility. However, in order for the simulation model to be an accurate representation of the true-to-life system of the machine, it is of most importance that all the data gathered is as accurate as possible. This was achievable since access to the existing plant and expert's opinions were readily available by telephone or email enabling frequent and fast response as and when needed.

The focus of research is firstly to understand the current processes and parameters of the crusher machine and the core reasons behind a breakdown occurrence. Prior to the development of any maintenance model being carried out a thorough understanding of the processes concerned is critical. Insufficient and irrelevant information in this area will most certainly cause adversity in the task of understanding the problems under scrutiny. When understanding the processes involved it is equally important to consider the tasks carried out at inspection and during maintenance. Only then, the replication of the model using Witness simulation can begin, after which the inefficiencies or problem areas by the use of *Witness* simulation can be identified. Research into other similar techniques used to reduce breakdown down times and inspection down times will be considered in order to develop greater understanding.

4.3 Research Design

Research will be carried out by means of consultation, emails, and meetings with reference to the historical data at hand in order to design and develop the first replicated model of the *Crusher* machine including parameters. Once the model is fully developed and a true to life system can be verified with real time data from the manufacturing plant, the extraction of results can begin to show the variations that exist.

The simulation model will help to identify key aspects in relation to machine breakdowns and manage potential changes before the actual application of new researched methods. The aim of this research is to develop a new potential machine breakdown-strategizing tool for the industry management to increase efficiency and productivity. This will decrease lead times and increase profitability, and enable the organisation to move towards a world-class performance strategy.

4.3.1 Data Collection Method

A field study was paramount to the entire collating of available information based on observations and consultations; this enabled the collection of historical data that had been gathered up over a number of years within the facility with regards to machine breakdowns. The field visit enabled viable consultation and discussions with experts on the maintenance management team, the general operators and technical staff that carried out repairs. Field research developed the core understanding of the machine and existing parameters as well as the technical aspects with regards to inspection and breakdown occurrences.

All the information would then be applied to the simulation model with the clarification of expert judgments on a continuous basis.

Case studies with reference to the techniques that will be used and implemented within the simulation model will be researched as to the use and further be discuss with experts to ensure similarity and viability before implementation.

4.4 Experimental Platform

This model will be based on the actual cement factory that exists in Libya. Currently, Libya is a fast developing country but still far from full development. The nation as a whole is finding it very difficult to compete on a global scale; especially the cement industry which accounts for the second largest portion of their economy after petroleum exports. Current production is at a 50% capacity and all production is consumed internally for the development of Libya alone with no emphasis on exports [52].

Unable to deal with the unexpected increase in demand for cement due to regional and national development plans, this has to a certain degree left the industry unable to meet demand and hence forced government and organisations to invest heavily into research and development. Libya has all the required resources for the development of products and exploration of new strategies to develop and create a strong industry. This industry could be capable of not just internal developments but also of being able to compete on a global scale with world class recognition in the future.

4.5 The use of Simulation

A poor plan or very good plan without the right implementation procedures can easily cause a ripple effect through the entire supply chain and further into other areas i.e. the Bullwhip Effect [53]. The overall effect to the entire business can be catastrophic. It causes cycles of excessive inventory and severe backlogs, poor product forecasts, unbalanced capacities, poor customer service, uncertain production plans, and high backlog costs, or sometimes even lost sales [54]. Hence, although the ERP, MRP and SCM solutions provide lots of benefits to industries, it is too costly to use those solutions for academic research. Further, the extracting of results without directly effecting the organisation due to the changes that will need to be applied will be very time consuming and excruciating. Simulation enables the replicating of the business model in a computer system totally risk free, as you can apply and make changes to the model, create “what if” scenarios to test strategic changes and extract results. The applying of changes to the existing business model only takes place in the system, where the replicated software model exist and hence has no direct affect to the actual organisation.

Simulation tools are designed to be used by human planners interactively, not as a real time decision making tool, which are directly linked to the control system to dispatch tasks. These tools aid the planner to make a right decision by providing information. Therefore, the planner should be able to interpret and modify the plan in order to achieve best performances.

Benefits of simulation are as follows:

- Enables the evaluation of existing systems.
- Enables the evaluation of operating performance prior to the implementation of a system.
- Enables organisations to perform powerful what-if analysis, leading them to better planning decisions hence the

comparisons of various operational alternatives without interrupting the real system.

- Permits time compression so that timely policy decisions can be made.
- It helps to understand the overall management and maintenance processes and characteristics by visual graphic/animation.
- Able to capture system dynamics, using distributions, user can model unexpected events and understand the effects thereof.
- It could dramatically minimise the risk of changes in planning process, by what-if scenario simulations, user can test various alternatives before changing actual plan.

4.6 Bayesian Network Modelling

The Bayesian model allows important information to be considered with reference to key influencing factors on the failure of the crusher machine. The addition of these influencing parameters has given a superior depth of understanding to the probability of failure, resulting in a greater confidence in the overall results of the simulation model. Three influencing parameters, which result in the breakdown of the crusher machine, have been used for this study. These are the drill head, dusting and lubrication. The historical data gathered for each influencing parameter together with the expert judgement has been carefully scrutinised and applied to the Bayesian network model.

4.7 Breakdown Distributions

The models of the *Crusher Machine* taken under consideration for this thesis are built in WITNESS simulation software (Lanner Group) previously used to develop the entire manufacturing plant. From which, only the crusher machine has been chosen due to the major disruptions it caused every time it would breakdown and the individual importance and value it holds within the process of cement manufacture.

Historical breakdown duration data for machines are available directly from the maintenance management monitoring system from which the mean time between failure has been extracted and used to develop and test model. The collected data need to be validated by deleting unreasonable information according to observation from field research and expert consultation. This must be checked for relationships before the data can be used in the subsequent analysis and transformed for further analysis in the breakdown modelling process.

Lanting Lu [10] proposed using fitted mixture distributions for groups of machines to represent the machine breakdown durations, i.e. the time to repair machine failures. This is because it copes well with the multimodality present within the data and can smooth out its irregularities. For the purpose of this thesis however, as the modelling is only conducted for a single crusher machine that exists within the entire process (rather than groups done by Lanting Lu [10]), the breakdown modelling process shown in figure 4-1 will be used, which consists of three major requirements but however will only use the first two requirements as follows:

- Data preparation and transformation:

Modifications need to be made to validate the data for breakdown distributions fitting process.

- Select breakdown distribution type:

The type of distribution should be based on the classification of the breakdown duration data. A negative exponential distribution is considered to be the most appropriate to represent machine downtimes because data has been extracted from over a period of 3 years that can be seen in appendix E from which 3 separate months have been scrutinised in order to extract the time between failure from which the lowest and highest amount of time has been considered.

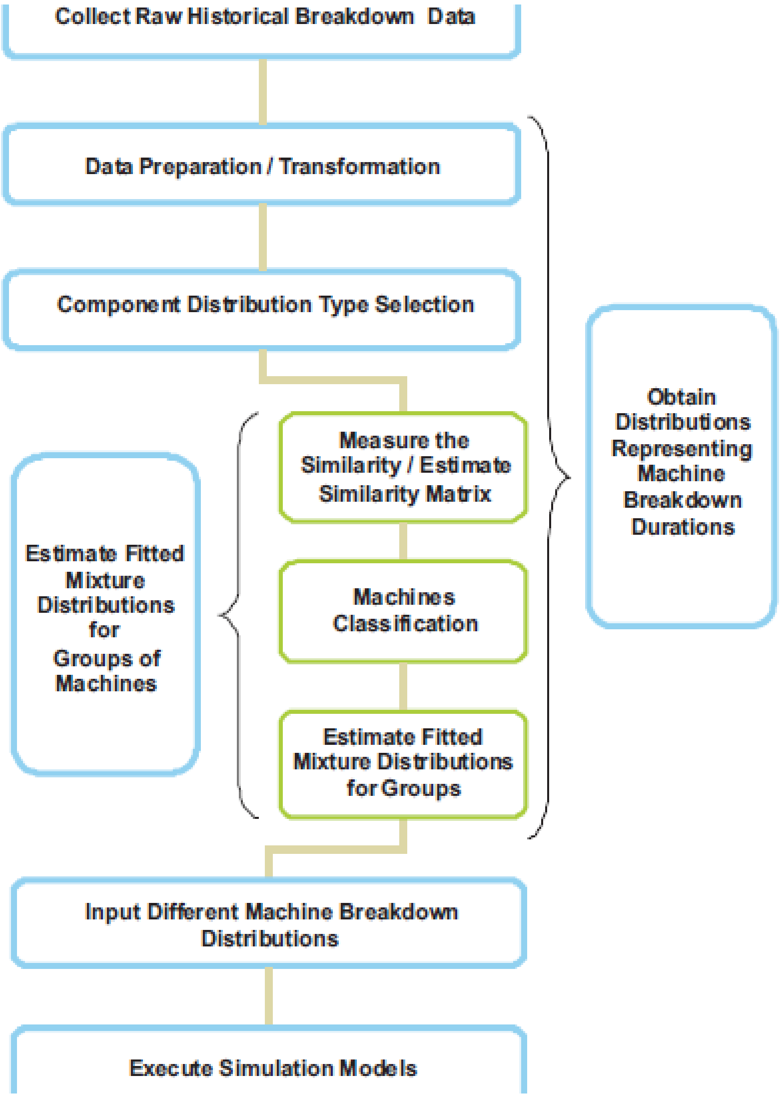

Figure 4Breakdown Distribution of industrial machines, Lanting Lu, etal [10].

4.8 Organisational Challenges

The organisation is currently facing problems with running below capacity, not being able to keep up with demand due to increase lead times as a result of inefficiencies throughout the organisation in many areas. Therefore it is very difficult to pin point exactly where attention should be concentrated.

The lack of education and training at all levels of the industry is also prevalent due to political bureaucracy and the working culture from past generations which has been imbedded within the existing system making change very hard.

The organisation is currently having major problems due to the age of the machinery, which may need to be looked into further as whether they should carry on using and repairing as and when necessary or simply scrap certain machinery as a whole.

One of the main challenges the organisation will face in the future is not that of the development of new strategies and methodologies to increase capacity but rather the implementation of such strategies or methodologies within the organisation i.e. J.I.T, SCM and TQM etc.

4.9 Research Method

- Establishing research on machine and existing parameters (Field Research [10]).
    - Develop a balance of objective and subjective information based on expert knowledge.
- Develop list of assumptions for creating model to gain a true to life system.

- Implement all research into WITNESS simulation programme to enable model building.
- Use Witness replicate actual crusher machine.
- Implement the Mean Time between Failure stoppages into Witness.
- Finalise and test simulation to assure all processes are efficient and in working order according to research.
- Identify problem areas and processes within the simulation model with reference to research ready for consultation.
- Record all results and compare to existing crusher machine data.
- Apply the Bayesian Network Modelling strategy and equations to the simulation model.
- Research further if viable changes can be applied to the model via consultation to achieve a true state in the model.
- Compare and analyse the results of the Mean Time Between Failure model and the Bayesian model with reference to available information and expert opinions.
- Test and validate the simulation model using a stochastic approach.

- Recommend applicable changes that can be applied to enhance performance.

4.10 Project Plan

The project plan can be demonstrated via the use of a simple 5-step approach shown in figure 4.2; these steps enable an implementation of a flow system where the plan starts at observation from which all the data is gathered from i.e. research paper [9].

Figure 4 5 Step Approach system for project planning

The 5 step approach allows the observation and data to be gathered, after which implementation into the model can be made. Once the model is at a satisfactory state, evaluation of the model can take place. Thereafter "what-if" scenarios can be developed in order to observe further. This cycle can be followed as many times as necessary until the model is fit for the purpose enabling an adequate amount of testing and changes to be applied where needed. Hence the requirements of the following points:

- Research the cement industry and cement production in general, using books, journals, company reports and the use of the internet.
- Research philosophies and techniques such as Supply Chain Management, J.I.T, Total Quality Management, Culture-Structure-Systems, MRP, MRP11, World Class Performance and Bench Marking strategies.
- Continuous consultation with experts on the field and employees of the cement industry.
- With the above research and further consultation, the building of the simulation model will begin and a logical representation of the machine will be developed.
- The recording of all the findings from consultation with experts and the tests will need to be noted for means of comparison and effects.
- A full comprehensive report will need to be written regarding the changes applied the effects thereof and the results achieved.

4.11 Conclusion

This project will demonstrate a model via the use of witness simulation software, the model will mirror the cement factory *Crusher Machine* that they have in place, from the model created, and the *Mean Time Between Failure* approach will be applied based on historical data. Thereafter, changes will be made to the model according to findings to improve performance without jeopardising the quality of products. This will form the second model where the Bayesian Network Modelling will be applied to the existing parameters and conjoined to represent the *Crusher Machine*.

4.12 Summary

This chapter highlights the methodology used in carrying out the necessary research with relevance to machine breakdowns and the tools used to combat this problem. It presents the stochastic and discrete event programming solution to machine breakdowns via the use of integrated analytical tools. The solution provides a dynamic alternative with a visual reasoning behind the occurrence of breakdowns. A number of different data capture methods are incorporated and the chapter finishes with the advantages and limitations of the methodology presented. This chapter highlights the research that is needed, the structure the research will be undertaken in, the experimental platform and the benefits of using Simulation modelling.

Chapter 5

Modelling the Problem

5.1 Introduction

Witness simulation modelling can be a complicated and technical systems analysis and management strategy, where the success of the required implementation depends as much on the research undertaken and experience developed in using Witness as the actual problem at hand that needs to be simulated. This requires good project planning and management techniques in order to implement and program research into simulation and thereafter make changes where needed to be able to extract the most accurate results.

The initial steps include a thorough analysis of the problem being researched that enables an accurate representation to be made. This representation is firstly sketched on paper where all elements required are highlighted in terms of what they will represent and then elements are connected together to form the model on paper. Once the analysis has been fully carried out, it should produce a systematic layout that can be used to develop the model.

This enables a representation to be as accurate as possible according to the layout and elements analysed, after which a computer simulation can be developed accordingly to verify the preliminary performance results. Once the simulated model and extracted information from therein is at an acceptable level, i.e. the simulated data match that of the research field data of the problem, the model can be considered a good fit and hence allow the programmer/researcher to make accurate judgements about the aspects of concern in any given investigation.

The size of the simulation model is not dependent on the size of the problem but rather on all the small elements that make the problem possible. The size of the simulation model can also be dependent upon the size of the project/research, which may take into account an array of different aspects from start to consider all the detailed actions required for the model. Many a times, the size of a simulation model is much smaller than expected due to the model being developed with assumptions that enable many facets to be abolished.

For the most accurate true to life representation, the programmer is expected to thoroughly detail all interactions between all component elements within simulation model. Witness simulation modelling can also be dependent upon the different types of research, hence it is very important to know the nature, scope and demand of the actual requirements needed for the model.

Important points need to be noted such as:

- What is required in the model?
- What are the basic inputs?
- How many activities are needed for model?
- What should the elements represent?
- What are the basic outputs?

- What results are expected?

- What is the behaviour of the model?

An array of simulation package tools are available namely, Pro Model PC, SIM FACTORY, Extend Sim, ARENA however the Witness package was selected for this research purpose due to previous experience with this software enabling better understanding and development.

5.2 Why Witness Simulation (Lanner Group)

Witness simulation software was selected due to its powerful dynamic graphical user interface that has been used in many different industries for various purposes. Witness was also chosen due to the previous experience of the software that was at hand enabling greater understanding. The simulation software enables model building using an array of elements to represent almost anything. There is then the opportunity for, flow and link between elements, discrete distribution availability, powerful yet simple programming features such as logical conditions namely If, Else, And etc. Witness also provides a fully integrated automated response system that can be manipulated for the benefit of the user and the availability of vast amounts of statistical information that can be extracted upon request for every individual element that exists within the developed model. Complex situations can be adhered to that are very time consuming to implement without significant disruption. These can be solved by Witness simulation package through its powerful features of visual experimentations and the development of what if scenarios that enables the user to make changes as needed.

Users can define procedures, functions, distributions and have the abilities to solve an array of complex problems. To ensure the success of any project in any industry Witness simulation package has several unique aspects and abilities to complete any complex project successfully from implementation to results by using a practical methodology.

The simulation software enables business process improvements for world leading organisation namely BAE and Toyota. It enables managers to model, analyse and optimise processes to make superior decisions in a risk-free environment. Witness simulation is the key to improving productivity, efficiency and reducing costs affectively without making any direct changes.

5.3 Simulation Approaches

After a thorough analysis, that enables the nature and requirements of the project to be decided, the next decision will be the type of simulation that should be used to find the solution and what sort of statistical issues are involved to best suit the overall requirements of the entire project at hand.

There are four approaches to model building as follows:

(1) *Stochastic* - This simulation model has one or more than one random variable as an input, since a random input generates a random output. Its elements are sometimes associated with probabilistic elements..

(2) *Deterministic* – Unlike the above, this approach contains no random variables. It requires a known set of inputs that result in a unique set of outputs. Hence, absolute statements relate to the elements. For example, the load entering the crusher machine can be specified.

(3) *Discrete Event Modelling* – This is simulation modelling in which the state variables change only at a countable number of points in time. The relationship is discrete and random rather than smooth and predictable.

(4) *Continuous Simulation Modelling* – A simulation in which the state of the variables change continuously with respect to time.

This thesis will use a combination of discrete event simulation and stochastic modelling due to the nature of the research and problem that needs to be modelled.

5.4 Developed Witness Simulation Models

Three different models were developed as follows:

1. *Mean Time Between Failure* (MTBF) model – which uses MTBF developed from the historical data and field research. This development models the number of times a breakdown occurs according to the MTBF in a 30-day period.

2. *Average Consumption Model* – progresses from the MTBF model as it is based on all the three noted parameters consuming above a desired average rather than a predetermined interval.

3. *Bayesian model* – uses a combination of objective and subjective data implemented and the probability of failure based on Bayesian Network Modelling aided by Hugin software that is dependent on the existing parameters.

5.5 Basic Assumptions

The simulation model developed will be based on various assumptions; and hence, a list of assumptions was made so that the computer simulation could run alongside the physical system irrespective of minor differences. This is also to ensure the smooth operating and the ease of programming, as certain characteristics do not need to be considered in order to give an accurate representation of the actual machine and its parameters.

Basic assumptions for process and flow are as follows:

1. The three parameters i.e. drill head, dusting and lubrication, are represented by separate entities.

2. All parameters are readily available on hand.

3. The *Inter-Arrival Time* of the entities is of no significance due to point 2

4. All parameters move forward to their designated *Queue's* respectively and wait until needed.

5. The Queue's have a capacity of 5 as they only represents points 2 and 3, almost like a storage unit and no further responsibility or representation.

6. Each parameter moves forward to the designated activities named *Crusher, Crusher01* and *Crusher02.*

7. All three activities combined together represent the single *Crusher Machine*.

8. After the parameters have consumed their given life span, they move forward to exit the system via means of a conveyor.

9. The conveyors sole purpose is to allow more than a single parameter to exit the activities simultaneously as sometimes if more than a single activity tries to push out a entity, it can cause unnecessary blockades.

10. Operators are fully qualified and experienced in undertaking any sort of maintenance required.
11. Machine is established to be as good as new after maintenance has been carried out.
12. Bottlenecks do not exist in the supply to the machine neither the supply from the machine.

The basic assumptions allow a smooth flow of all elements throughout the developed system.

5.6 Basic Model

To attain a close match of the actual crusher machine and existing parameters is of crucial importance in order to compare the behaviour and results with the research information gathered. The developed simulation should run accurately and mimic the physical representation of the machine irrespective of minor difference.

Witness simulation provides a platform to map the logical model into a developed simulation model. Modelling starts with basic elements according to the requirements of the problem and research and utilises different elements to solve the problem.

The Witness programming software uses basic elements, together with distributions and timing inputs to replicate an accurate model. The distributions are then used to influence certain factors so as to acquire a certain result.

The basic elements used to simulate the models are as follows:

Entity: Entities represent parts that flow through the model, in this case, parameters that have to be used in order for the machine to function properly. Hence the parameters wait to be consumed by the machine after they move forward and exit the system once they have been consumed. Further example includes:

a. A project progressing through a large corporation.

b. Calls being received and answered in a call centre.

c. Application forms being processed from within an office.

d. People moving through shops etc.

Activity: An Activity is a station where a task is completed, for example, the location where the parameters are being utilised. in this model they represent the crusher machine collectively. Further example includes:

a. Many typical stages in business processes.

b. A counter position in a shop.

c. The Handling of an email enquiry.

Queue: A Queue is a point where an entity is held until the entity is required or needed, or even a point where a desired waiting time can be applied. For example, the parameters have to wait until the previous parameter has exited the crusher machine. Further example includes:

a. Files waiting to be processed.

b. Customer in a queue waiting to be served.

c. Materials waiting for other materials to arrive.

Resources: Theses can be the labour required to perform a desired activity, and are often important and necessary to perform certain operations. These can be people or physical equipment that may be required by other elements for processing during simulation for example, a specialist technician required for machine repairs. No resources have been used in this thesis. Further examples include Operatives, Technical staff and Managerial staff.

Conveyor: A transporting or moving element, which enables an entity to move from one location to another continuously i.e. when the parameters leave the crusher machine after being consumed. Further example includes:

- Parts moving on a conveyor belt

- Raw materials moving from one machine to another

- People moving on escalators

Some simulations elements within the actual modelled system are shown in table 5.1 as an example. When these elements are linked together in sequence, Witness simulation allows the process to flow accordingly. In order to develop the simulation model as accurately as possible, information of all elements and applications were studied thoroughly

Table 5. Simulation elements description and representation used within the model

Element	Description in Model	Representation
ENTITIES	Raw Materials Lubricant Drill Head Extract Dust	Raw Materials Operator Task Machine Component Operator Task
QUEUES	Q001, Q002,Q003	Operator Task and Component Storage
ACTIVITIES	Crusher Machine Dummy	Phase 1 of crusher machine Machine used to calculate pass and fail ratio Dummy activity used to implement equations

Witness simulation enables the user to define many aspects of the model by applying variables and attributes to different elements accordingly, as and when required.

Variable: A variable contains a value (or a set of values, if the quantity of the variable is greater than 1). When defining a variable, it must also specify its data type, which indicates the type of data that it contains.

The types of the variables are:

Integer - The variable contains a whole number.

Real - The variable contains a number with a decimal fraction.

Name - The variable contains a WITNESS element name.

String - The variable contains a string.

Attribute: An attribute is an element that represents a characteristic of an individual entity, resource, activity or carrier element. For example, you could use an attribute to characterize colour, size, skill, cost, density, voltage or serial number. An element's attributes can change value during the course of the simulation. For example, the colour attribute value of an entity could start as gray, change to red after the entity has passed through a painting activity. Attributes have to be user defined according to suitability.

Table 5. **Witness variables and attributes use and purpose within the model**

Variable	**Use**	**Purpose**
Inspection Down Time Breakdown Time	Take into account all aspects of time i.e. inspection / breakdown time, resume time, average time , total time etc.	Provides an efficient account of when, how long, average time and total time of occurring events took place.
Attributes	**Use**	**Purpose**
Breakdown Time Repair Time Life Span	Applied different durations to elements according to requirements	Run accurately according to the findings of the research

5.7 Basic Model Building

Figure 5-1 shows the actual programming software which looks like (on a computer screen with no actual programming) a plain screen. However it does show the four basic elements that can be applied to the programme i.e. Entity, Queue, Activity, and Resource. The analogue clock that is visible at the right hand bottom corner enabling programmers to manipulate timing within the model and see the different variations on time applied.

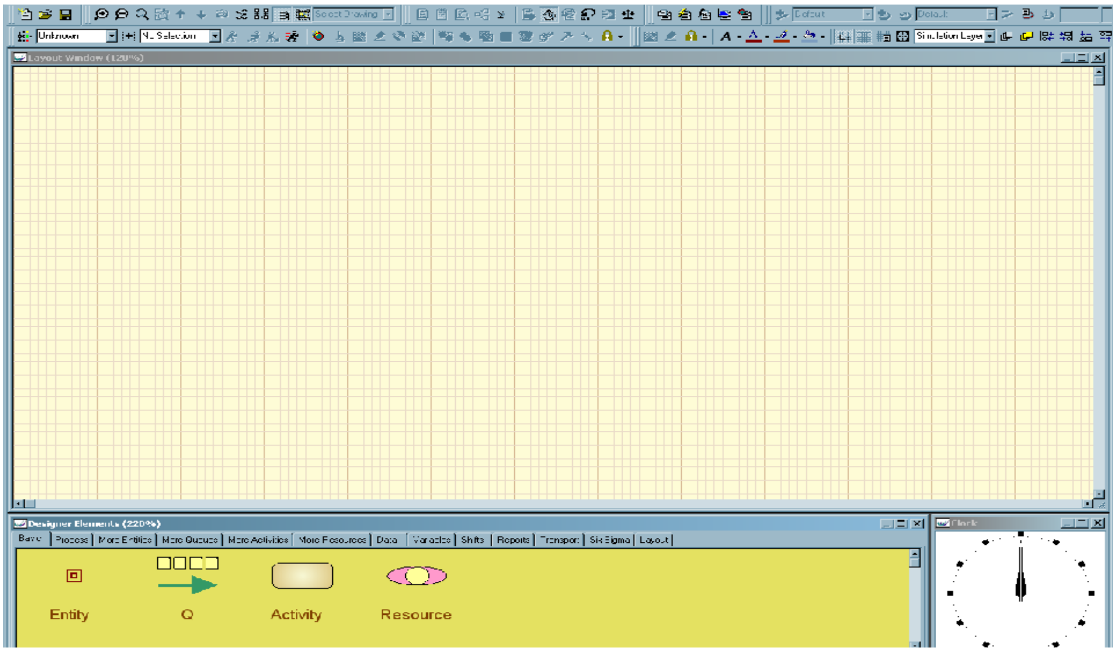

Figure 5 Witness Simulation Plain Visual Aid

These elements can be applied to the programme by a simple a push of a button on the mouse on the desired element and then clicking on the grid lines on the screen where ever you may wish to put the element. What follows is a step by step process of the implementation of Entities, Queues, Activities and Resources.

5.7.1 Inserting and defining Entities

To insert an entity into the system requires one click on the entity and another click on the screen enabling the programmer to put the entity on the desired location wherever it may be as can be seen in figure 5.2.

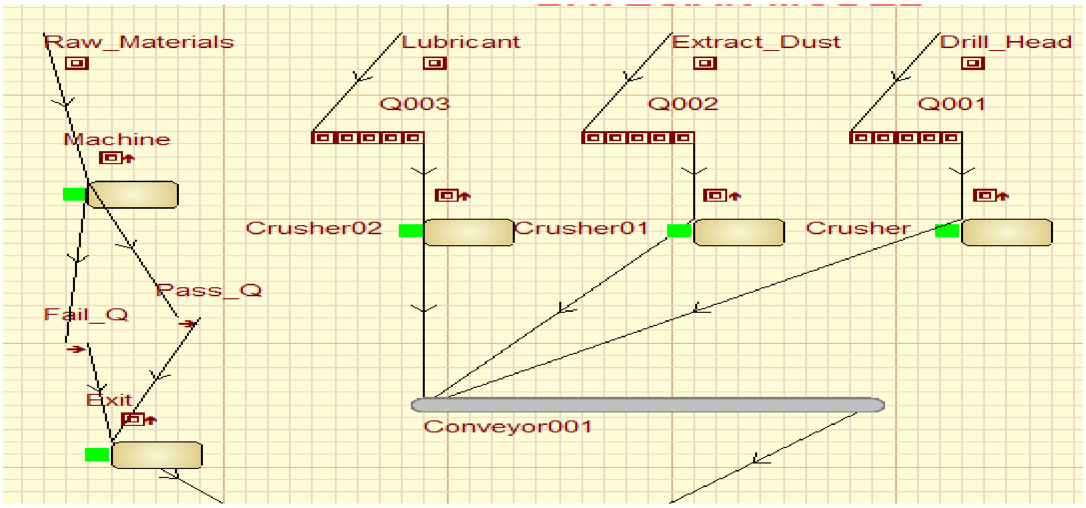

Figure 5 Inserting an entity using Witness

Figure 5.3 shows how the entity is activated: double click on the Entity shown in figure 1 and then a box (figure 5-3) appears. This enables the user to change the name of the entity for example, customer as in figure 5-3. Click on the **Type**, decide whether the entity is to be ***Passive***, which enables the entity to pass through the model, or ***Active***, enables the entity to have specific arrival time and specify the number of entities as well as an inter arrival time between entities that can be seen in figure 5-4.

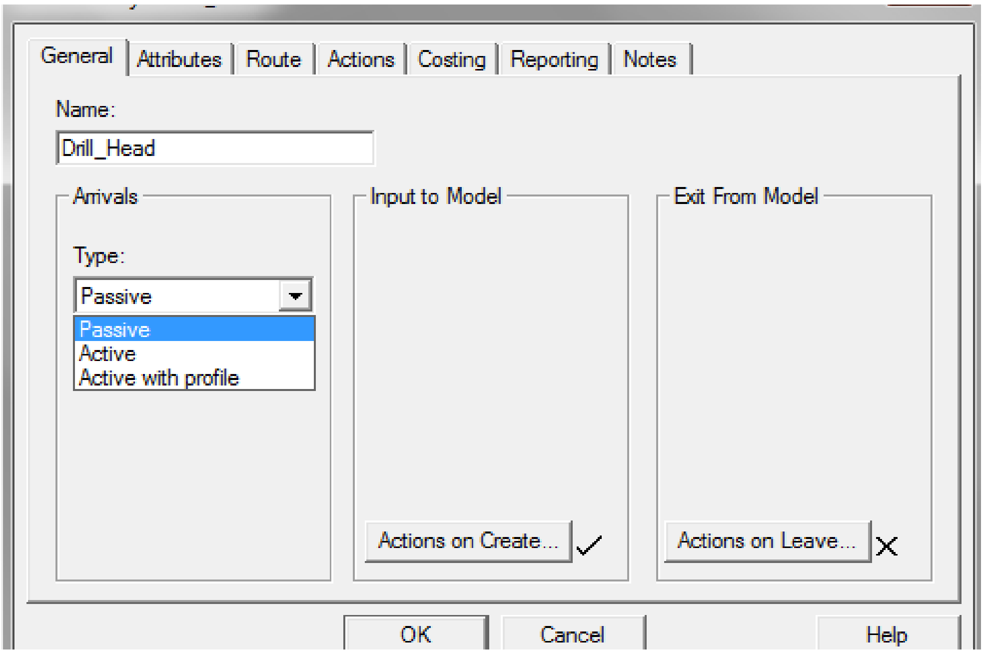

Figure 5 **Detail entity and choosing entity Type**

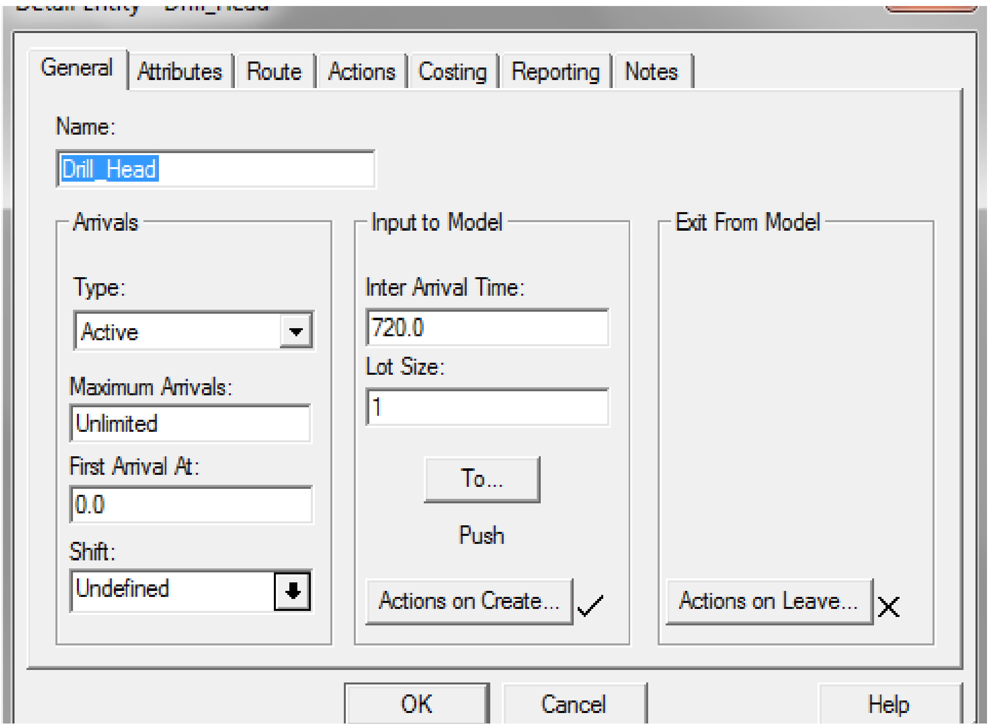

Figure 5 **Detail entity and applying entity type when active**

5.7.2 Inserting and defining Activities

A single click on the activity and another click on the screen enable the programmer to put the activity on the desired location as shown in figure 5-5.

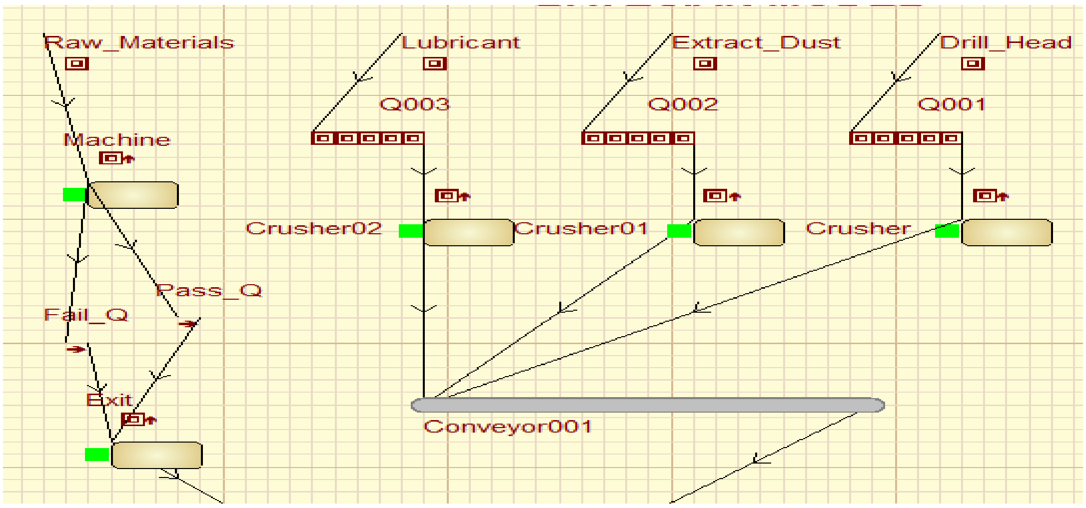

Figure 5 Inserting an activity

Figure 5-5 shows the tabs available that can be used to manipulate the activity according to need. The user can apply changes and implementation requirements to all the available tabs. Therefore, setups, stoppages, shifts etc, can be applied to any desired activity according to representation.

Similarly, all other elements have similar options that can be manipulated to fulfil the requirements of the projects.

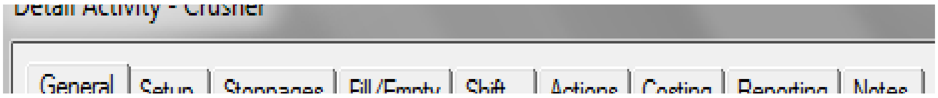

Figure 5 Detail activity options available

Double click on the activity and the detail activity box appears as shown in figure 5-6, it enables changes and the application of a variety of different programming concepts including the name of the activity. The user can add a specific duration that entities should spend on the activity and specify the resources required to carry out the task, input of formulas as entities arrive and leave. Actions on start of the activity and actions on finish allow further programming to be inputted into the activity itself. The quantity of activities required can also be specified according to need and the project plan.

The software allows user to decide what type of activity should be carried out i.e. click on ***Type*** as can be seen in figure 5-4 and the drop panel should appear giving the following options: single, batch, join, split, multiple task i.e.

what the activity should do with the entities that arrive with the option of a multiple station.

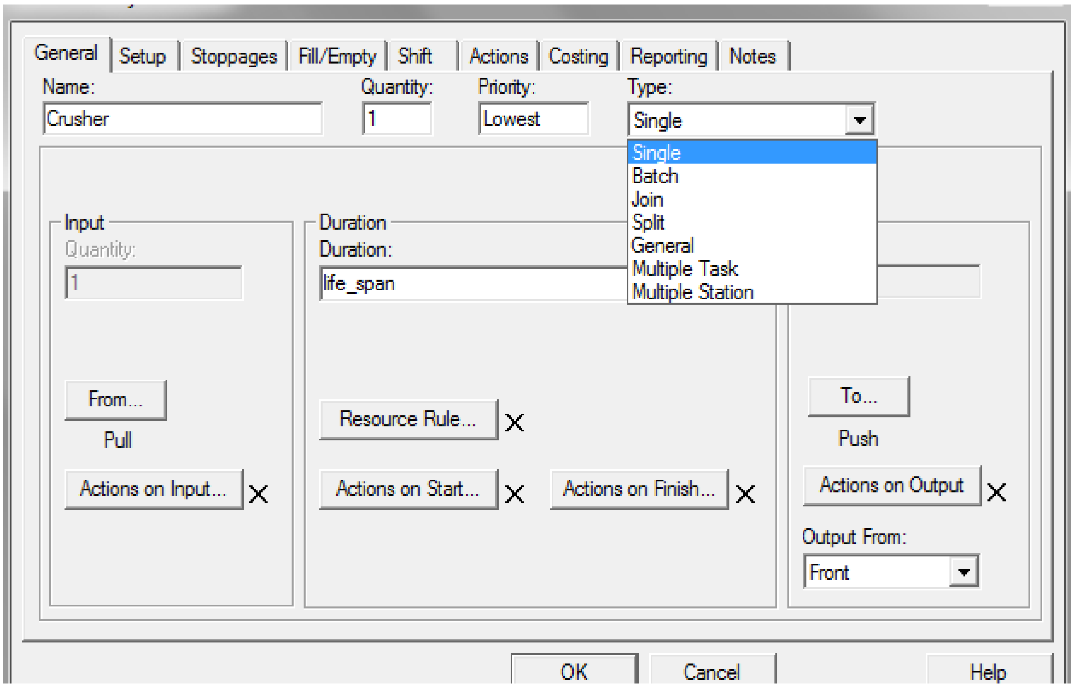

Figure 5 **Detailing an activity from start to finish**

In figure 5-7 the entity flow, where the entities come and where they should proceed to i.e. ***From*** and ***To***, programming at this stage also allows conditions to be set and entities to flow accordingly and not just ***From*** and ***To***.

5.7.3 Inserting and Defining Queues

One click on the Queue and another click on the screen enable's the programmer to put the Queue on the desired location jus as the entity and activity. Figure 5-8 shows the existing queues in the model.

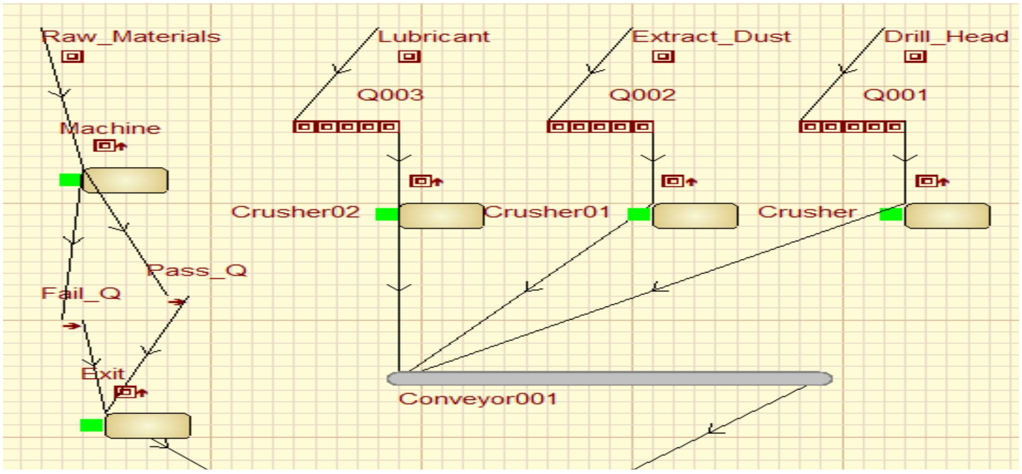

Figure 5 Inserting Queues

Double clicking the Queue enables the detailed setup of the queue as shown in figure 5-9. This enables the change of name, capacity and the quantity. The desired duration that entities should spend can be specified. Formula's can be inputted as entities arrive and leave in the actions on input and output tabs. The arrows indicate the entity flow i.e. where entities come in and where they should go out to. A delay option is also available to enable entities to spend a desired amount of time just like the activities before they move forward.

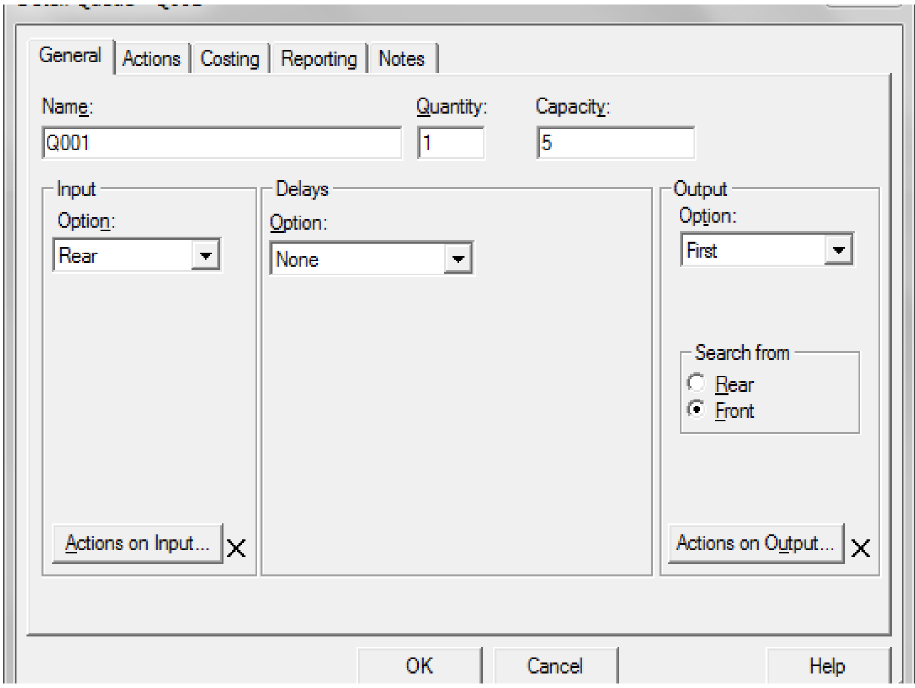

Figure 5 Detailing a queue

5.7.4 Inserting and defining Conveyors

The conveyors are applied to the system exactly as the other elements, however in order to locate the conveyor and other transport systems that the software has, click on the ***Transport*** tab on the Designer Elements as shown in figure 5-10. This shows all the different transport systems that can be implemented for the desired requirement of which conveyor has to be clicked on and then back on the main screen.

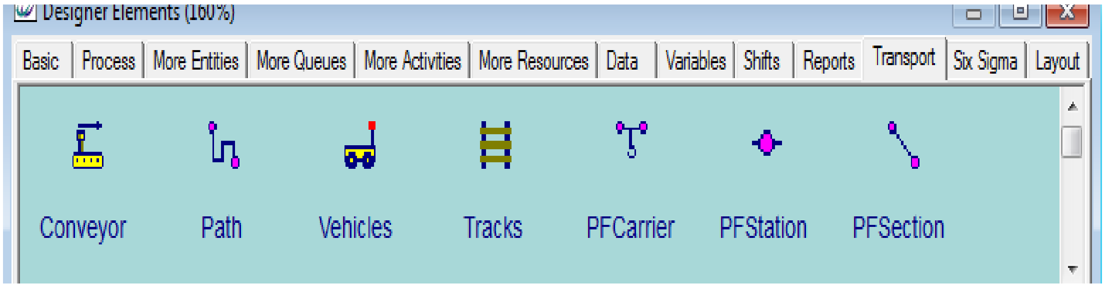

Figure 5 **Choosing Designer Elements - Transport**

Once the conveyor has been placed within the system, adjustments can be made as to how many entities there are and the movement times. Further rules can be applied if necessary as entities enter and leave the conveyor systems, this can be seen in figure 5-11.

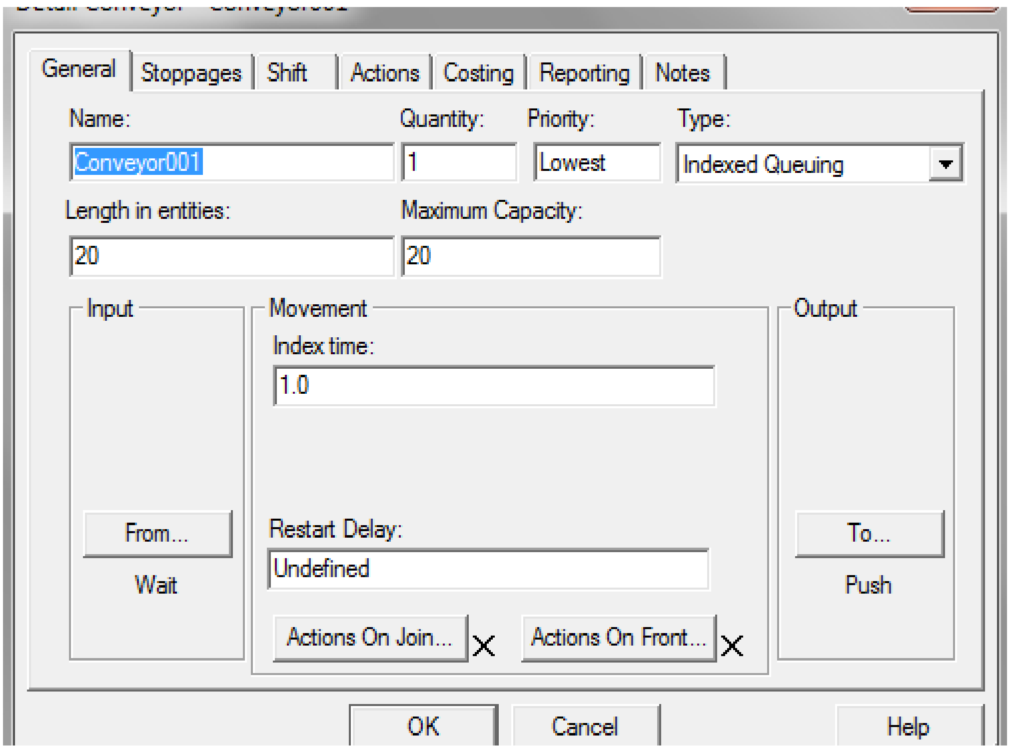

Figure 5 **Detailing a conveyor**

5.7.5 Joining of Elements

Once all the required research was undertaken regarding the crusher machine and existing parameters, the modelling was started. Continuos' adding of relevant entities, activities, and queues was performed in a manner that replicates the necessary processes that apply, as can be seen in figure 5.12.

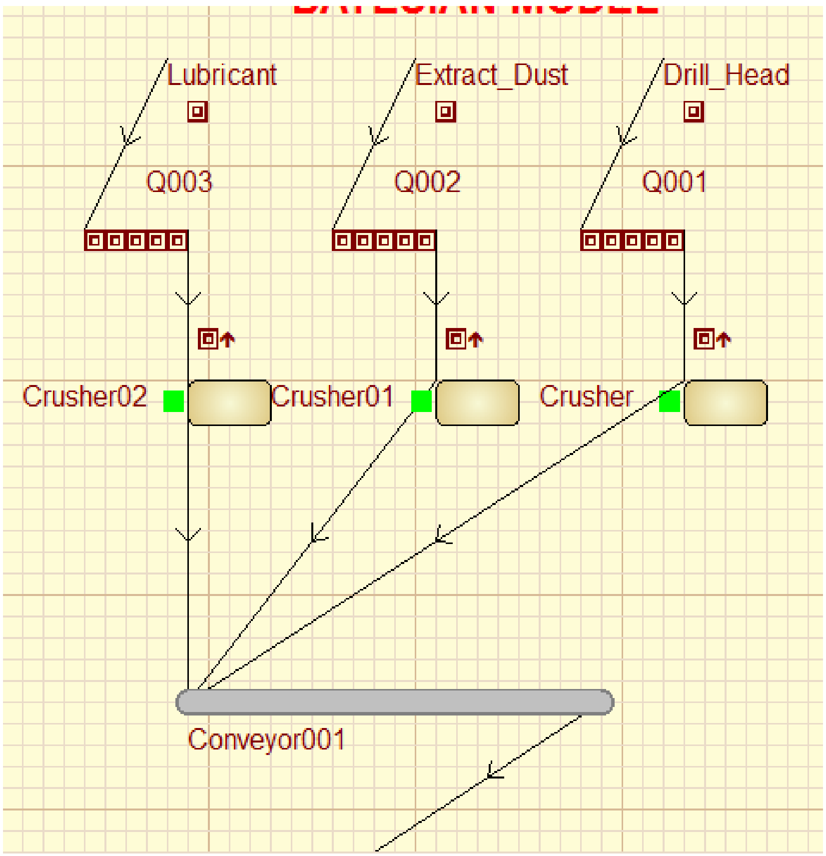

Figure 5 **Representation of Crusher Machine in simulation model**

All the elements of the model in figure 5.12 have been given names accordingly to identify them separately for their purpose and for programming needs. The graphic details can also been updated (although this is not necessary) and introduced into the model. This can simply be done by right clicking on an element and clicking the update graphic tab where it leads to further tabs according to elements. This is shown in figure 5.13.

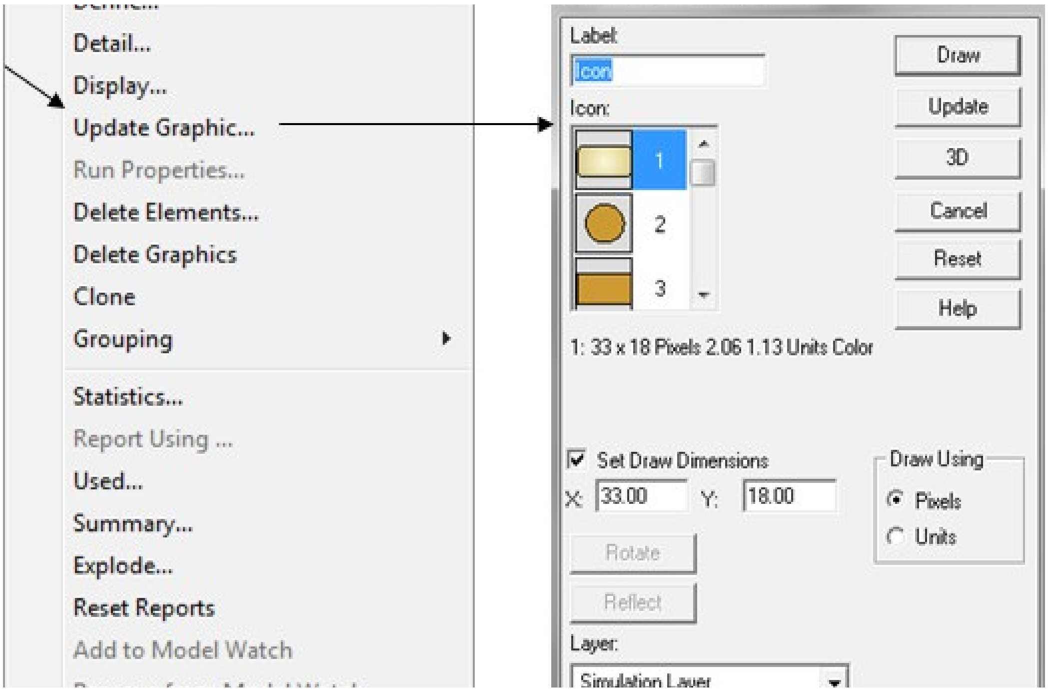

Figure 5 **Updating graphical representation**

Text can be implemented in the same manner as and where needed as can be seen in figure 5-12, where the entire model is shown and various text is visible according to need and identification of elements.

The next step was to join all the elements respectively, direct where the entities should go and how long they should spend designated locations, and determine if the need of a resource exist i.e. operator and/or technical staff. For example, when the drill head needs changing an operator and technical staff are required.

Once all the relevant entities, activities, queues and resources were in place, it was very important to make sure all the entities moved where they were needed and according to the processes, they represented. It was also necessary to make sure all the entities spent the required time at locations and setup and stoppages were in working order.

This can be seen in figure 5-12 represented by all the lines visible going from one element to another, in order to do this, the element was selected and then the PUSH TO/visual Output Rule button  or PULL FROM/Visual Input Rule button , was clicked and the relevant element was selected. This way all the entities that represent parameters move forward to queues after which they are pulled by the crusher machine according to need. Once usage rate is consumed, they move forward to the conveyor and out of the system as shown in figure 5-12.

The push and pull rules can also be seen in figure 5-14 and 5-15 respectively.

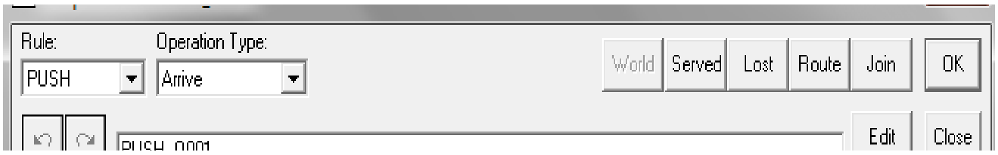

Figure 5 Push Rule (Drill Head to Q001)

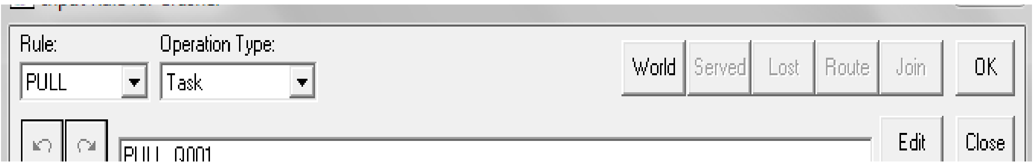

Figure 5 Pull Rule (From Q001 to Crusher)

This is the simplest form of applying the PUSH and PULL Rules to the elements to make sure they go to their designated places. Further Rules can be applied govern how they proceed forward from one element to another which shall be highlighted later on in specific areas within the model that are applied via the input and output, from and to tabs shown in numerous figures when detailing elements.

Resources are also implemented in the same manner, double clicking them enables changes to the names or- update graphics and these resources can represent operators or technical staff etc. The resources are then allocated to the required workstations by inserting a specific rule into the ‘Resource Rule’ button shown in figure 5-7, detail activity. However, this model does not consider any resources as this aspect will be overlooked via the use of assumptions which the model will be based upon and which will be highlighted at a later stage. Further, a resource is used named operator to calculate the duration of each parameter with respect to its given life span based on research data [9]. This aspect has been implemented with a certain programming technique and will be highlighted in further detail at a later stage.

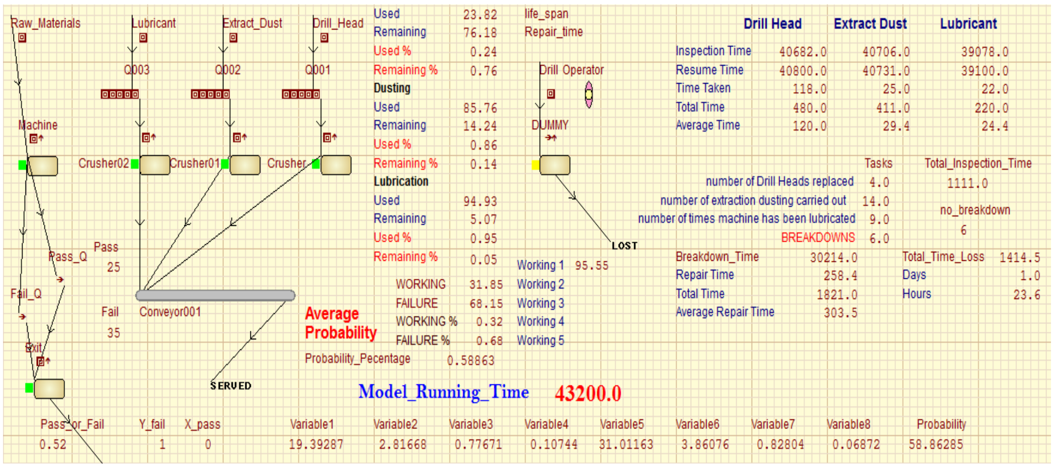

Figure 5 **Entire Modelled System of Crusher Machine**

The crusher machine is an intensive industrial machine that works non-stop if possible. Raw material is put in the crusher machine directly from the quarry. The crusher machine consist of one single part that is of most importance namely the drill head which is used to crusher huge rock formations to small particles. And a further two tasks need to be carried out by operators in order to keep the machine in a healthy working order to prevent breakdowns. Hence, the 3 parameters represent tasks that need to be carried out on a regular basis on the machine within the cement manufacturing plant [9] as follows:

A. The *Drill Head* has to be changed every 7 days.

B. The *Lubrication* of the machine has to be carried out every 3 days.

C. The *Dusting* has to be carried out every 2 days.

Hence, the tasks are represented by individual entities as can be seen in figure 5.16 and figure 5.10.

Tables 5.3 and 5.4 show the representation of each element within the simulation model with a little description and purpose.

Table 5. **Key Representations of Entities and Queues in simulation model**

MODELLED ICON	REPRESENTATION
	Represents the parameter 1: *Drill Head* which actually is a replacement task
	Represents the parameter 2: *Dusting* which is a cleaning task
	Represents the parameter 3: *Lubrication* which is a cleaning task
	Represents a dummy entity which calculates time and is applied to the dummy activity to enable further programming. This entity has no direct influence on the model.
	Represents raw materials that enter the machine activity to calculate pass and fail ratio. This entity has no direct influence on the model.
	Represents a storage point within the model for parameter 1.
	Represents a storage point within the model for parameter 2.
	Represents a storage point within the model for parameter 3.
	Represents the flow where raw materials that are classed as`_ pass_` go through.
	Represents the flow where raw materials that are classed as _`fail`_ go through.

Table 5. Key Representations of Activities, Conveyor and Resource

MODELLED ICON	REPRESENTATION
	Represents the location where parameter 1 enters which is part of the crusher machine.
	Represents the location where parameter 2 enters which is part of the crusher machine.
	Represents the location where parameter 3 enters which is part of the crusher machine.
	Represents the crusher machine and location where the raw material enter to be crushed for a certain duration before pass or fail ratio is generated.
	The dummy activity is the most important activity within the entire model as it enables the programming of many aspects as the drill entity enters every 1 minute.
	Represents where the raw material exit based on pass fail ratio, is used to pull entities from pass and fail queue with no real significance.
	Represents where parameters 1, 2 and 3 move forward to exit the system, enables more than a single parameter to be pushed from the activities which the parameters reside in.
	Is a dummy resource which represents and helps calculate time and consumption of parameters by the means of programming

Figure 5.17 is a visual representation of all the variables within the model in relation to inspection, tasks and breakdown. These variables have been made self-explanatory with the help of text as can be seen.

Figure 5 **Modelled variables in simulation model**

These variables help understand and enables further programming to illustrate model behaviour and the extraction of accurate readings with regards to inspection times (tasks times), the number of tasks carried out and breakdown occurrences and durations therein.

Similarly, witness simulation consist of its own visual interact box as can be seen in figure 5.18 This enables the programmer to apply automated messages that pop up based on certain situations. Figure 5.18 is the actual automated response system of the model. The user is able to specify message, colour and time for the purpose of clarity and representation. For example, the colour green represents Dusting, yellow represents Lubrication and blue is for Breakdown occurrences. Every time a task is needed to be carried out (i.e. when the life span of the parameters has been consumed fully), a message appears indicating task and the time of occurrence. Further, once the tasks have been completed, other messages appear indicating completion and the specified time. This can all be seen in figure 5.18, and automated responses like these can be applied to the majority of places enabling accurate results to be extracted.

Figure 5 **Interact box displaying messages according to tasks carried out**

5.8 Summary

Chapter 5 describes the physical and technical procedures that are involved in the development of the simulation model. Simulation has been developed with the use of a set of assumptions from available data and the results extracted are approximate but close to real data results. *Witness Simulation* is a visual interactive interface enabling programmers and more importantly, management to see what happens at any given time or circumstance. Hence, simulations are the best tool to monitor and predict the future planning and development without applying any direct change or causing disruptions. This simulation is also based on a set of assumptions that are based upon the information gathered from research and provided by experts on the field. The selection of *Witness Simulation* was due to its powerful visual interface. It is a new generation of visual interface specially designed to deal with an array of complex problems used by many industry leaders such as Toyota.

Chapter 6

Modelled System

6.1 Introduction

This chapter follows on from the basic model development in chapter 5, which will be used as the base model. This gives the reader a deeper understanding of why certain entities and elements exist. Their purpose and what they intend to replicate from the historical data, expert knowledge and in relation to the techniques used i.e. mean time between failure and Bayesian network modelling. Presentation is accomplished with the help of many live screen shots, logical programming commands and functions are explained in greater detail with reasoning. After identifying all the necessary Witness Simulation element requirements and their functionality related to model development, the simulation models were developed. The *Mean Time Between Failure* model and the *Bayesian* model are introduced and discussed in further detail in order to develop and understanding of the differences in modelling and approach.

6.2 Mean Time Between Failure (MTBF) Simulation Model

The MTBF model is based on all the historical, observational and research data gathered in order to represent the existing crusher machine to the truest of nature. In order to carry out the model building accurately, many machine working processes/procedures have to be represented in a programming manner as will be discussed. The MTBF of the crusher machine is derived from historical data, it is based on the total machine run duration, divided by the number of times that machine has stopped, therefore MTBF = total machining time / number of stops.

Another very similar formula has been used by numerous authors to calculate the MTBF as follows, ∑ = (Start Time/Date of Last Failure – Start Time of First Failure) / (No of Failures – 1) [151]. Appendices A, B, C and E also show how this formula has been analysed with the historical data and developed in order to gather greater understanding of the MTBF.

The parameters used to derive the MTBF have been gathered from the field visit that consisted of observations, historical data, statistical averages and interviews as well as persistent dialogue with experts from the existing manufacturing plant. The data with regards to the crusher machine breaking down has been compiled over a period of 3 years, from which statistical averages have been derived in order to use within the models developed. Data can be seen in appendices A, B, C and E representing data from year 2008, 2009 and 2010 respectively.

All the values attributed to the models were derived and verified by the experts to be a suitable and an accurate representation as follows which will be highlighted in chapter 7.

Appendix A displays the data of the crusher machine from 2008, many more facets of data is available however not needed, all the important data has been extracted with care and the writing in red is additional calculated data the has been implemented due to need. Appendices B and C also show the same data but of different years as can be seen which has been used for comparisons purposes in order to come to a consensus with experts as to the best representation for the model in terms of variables. These tables actually dictate the input parameters for the models discussed in chapters 6 and 7, as variables from within these tables have been used to develop an accurate representation with the help of experts.

The tables firstly show the number of breakdown occurrences that have been segregated into months and the time that it takes for the maintenance team to return the machine to normal working order. The time is then added together to highlight the monthly time the machine has been derelict or the duration the machine has broken down for within a month as specified. From the tables it can be seen that majority of the months have 5 breakdowns however some months only have 4 breakdown occurrences. Further, it is very important to highlight, appendix A which represents 2008 is based on 365 days due to a leap year whilst Appendix B (2009) and Appendix C (2010) is based on 364 days. The number of days is important as it was used to calculate the MTBF. The tables show the number of hours spent on a monthly basis undertaking breakdown repair as well as a collated yearly sum after which an average monthly sum is highlighted.

The maintenance statistics highlight the input for the influencing parameters, their scheduled maintenance i.e. life span, and the time it takes for the maintenance team to carry out the scheduled tasks.

The data shown in appendices A, B and C enabled the development of an accurate representation of the base model as well as the MTBF model with the aid of expert opinions of which the results and experimentations will be discussed further in chapter 8.

6.2.1 Attributes Applied to Modelling

Each parameter has three attributes i.e. *Breakdown* represents the breakdown duration, *Life Span* represents the life span of each parameter (entity) and *Repair Time* represents the duration of time needed to carry out tasks. The three attributes shown in figure 6.1can also be seen in the actual model.

Figure 6**Attributes used in simulation model**

Each parameter is given its allocated duration by the development of an attribute named *Life Span*, this is the amount of time an entity spends within the crusher machine as identified in chapter 5 according to the research paper [9]. Once this duration is fully expended (duration representing the need for a task to be carried out), the activity will push the current entity out to the conveyor and pull a further entity from the queue. This action of change in entity represents the tasks that need to be carried out.   .

This aspect represents, the duration of time until a task is needed to be carried out i.e. the parameter drill head needs changing once every 7 days, and hence the life span of the parameter will be the same. This parameter (entity) will spend the given life span with the activity (crusher machine) until the time is consumed, after which a replacement will be needed that will be waiting in the queue.

The same will apply for all 3 parameters. They will spend their given life span respectively in their respective activity. This was the solution to creating the crusher machine, as one single activity cannot cater to the needs of all 3 parameters. The 3 separate activities that represent the crusher machine also allow further programming to be made individually for the purpose of parameters.

These attributes are implemented within individual entities enabling different durations to be applied at different locations within the model according to the parameters. For example, on the detail entity for drill head shown in figure 6-2 the attributes can be applied via the *Actions on Create* tab. This leads to a further *Edit Actions on Create,* where the attributed can be applied where life span = 10080, repair time = triangle (110, 120, 130) and breakdown = uniform (360, 420). These are the given durations for the entity (parameter) *drill head*. The same applies for the remaining 2 parameters as can be seen in figure 6-3 and 6-4.

Once the overall life span has been reached, then only certain tasks need to be carried out i.e. the drill head according to historical data needs to be changed every 7 days hence the life span is 7 days/10080 minutes. The dust builds up within the machine and can cause disruption or unexpected errors if not cleared every 2 days/2880 minutes and hence this is the life span of the dusting. The lubrication of the required mechanisms, , starts to dry and cause friction if not lubricated every 3 days/4320 minutes therefore the span is 4320 minutes accordingly. This can be seen in figure 6-2 and 6-3.

Figure 6 Applying rules on actions on create drill head entity

Figure 6 Editing rules on Actions on Create for Lubricant

Figure 6 Editing rules on Actions on Create for Extract Dust

All 3 parameters (entities) have different durations according to need and purpose, however the *Breakdown* attributes duration remains the same throughout. This is because when the crusher machine breaks down, all 3 parameters are at a derelict state and the repair time for a breakdown of the crusher machine is that represented by the combination of all three parameters, hence the same duration.

The attributes discussed have to be implemented within the activities that represent the crusher machine, which can be looked at as a workstation; therefore, as entities enter their designated activities, they are required to spend the allocated duration according to the attributes. The software will automatically apply the duration set by the attribute. This is the same case for the other two remaining parameters, which have different durations accordingly.

Figure 6 Specifying and applying the Entity Duration

Similarly, the attribute *Repair Time* has to be implemented with all activities, albeit in a different manner. Instead of the *General* tab shown in figure 6-5, the *Setup* tab is required shown in figure 6-6. This tab makes available a range of new options that can be applied to the activities in figure 6-5 where the important options, used, are indicated with of arrows. Once the user has enabled setups, the remanding options have to be adhered to, in order for the software to recognise what needs to be done every time a setup is required. This setup represents all the tasks and changes that need to be done i.e. the 3 parameters. The *Number of Tasks* and *Tasks to First Setup* have all been set to 1 as can be seen in figure 6-6. This is to ensure that actions are carried out at every single task rather than after a number of tasks, after the life span of each parameter, new tasks need to be carried out.

Figure 6 Setting up and applying detail to activity

After the tasks and setup have been chosen according to need, the implementation of actions can take place. Figure 6-7 shows the programming applied to the activity crusher for *Actions on Start*. Here you can apply any formula for the software to follow as soon as a setup has occurred i.e. figure 6-7 shows an *OPENBOX* rule that programs the automated response system to print out a message that should be according to the requirements of the model. At this point, the automated response system notifies the user that the drill head parameter has come to the end of its life span and is being replaced, giving the time of occurrence. A further counter system has been applied to calculate variables (timings) of repair as discussed in chapter 5. The same system is applied to all three activities in relation to all 3 parameters and their purpose. Similar is the case for *Actions on Finish* for all parameters shown, figure 6-8 applies actions after the tasks has been completed and has many more variables that take in consideration all variables of inspection which represents the carrying out of a task or changing of a part.

Figure 6-6 also shows where the attribute *Repair Time* has been applied, where the setup time is the repair time that the software will pick up according to the attributes discussed that have been applied to the parameters (entities). This will enable entities to spend their specified times according to actual repair times from all the gathered research and enable the system to take note at every change accordingly.

Figure 6 Applying rules to Actions on start for setups

Figure 6 Applying rules on Actions on finish for setups

This enables parameters (entities) to enter the crusher machine (activities), and spend their allocated life span after which a repair time would be applied, representing the time tasks take in order to carry out and all the processes will be noted via the use of formulae and the automated response system. This then allows the entities to leave the system to start all over again according to parameters.

The next step was to apply breakdowns according to the *Mean Time between Failure*, technique. This is applied in a similar process to that of setups. In order to carry out this procedure, the *Stoppages* tab is applied as shown in figure 6-9.

Figure 6 Applying Breakdowns details to activities

The applied stoppages will represent the machine breakdown process. Firstly, the mode has to be categorised as shown in figure 6-9 where it shows *Available Time*. This will make sure a stoppage (breakdown) can occur at any given time as long as the activity is available i.e. simulation model is running.

The *Time between Stoppages* is of great importance to the entire system; this represents the MTBF that has been derived from all the research gathered. All that needs to be done here is the MTBF ha to be inputted and the software will identify this and take further actions according to its programming.

Actions on Start for stoppages can be seen in figure 6-10, it is similar to that of *Setup*, and time is taken under considerations as well as the automated responses system to alert the user. The importance aspect in this action is the last two rules applied i.e. Breakdown (Crusher01) and Breakdown (Crusher02).

This rule ensures as soon as the initial *Crusher* activity applies the MTBF stoppage, the other two activities that represent the rest of the machine as a whole also come to a stop, as this rule is only applied to the activity named *Crusher.* The reason for this is that, if all three activities that represent the crusher machine were to be applied with the stoppage described and shown in figure 6-9, they would stop at different intervals as the software generates random values and further, the time between stoppages has been applied with a Uniform number allowing variations to occur as we have implemented data from the research that considers the minimum and maximum values.

The breakdown rule makes sure that all three activities come to a stoppage point simultaneously. Figure 6-11 shows the rules implemented for *Actions on Resume* for stoppages where the rule *Resume* has been applied to the other activities as well, in order to enable them to resume the normal working order at the same time after the breakdown duration has been adhered to. Further rules implement variables of breakdown and the automated response system to notify the user as to when the machine has resumed, indicated by the time of occurrence.

Figure 6 Applying rules for Actions on Start on Stoppages in an activity

Figure 6 Applying rules for Actions on Resume for Stoppages

This was the basis of the *Mean Time between Failure* model; where all entities (parameters) entered the system with 3 very important attributes. These attributes were extracted by the software as the entities move forward into the activities that represent the crusher machine, at which point the rules applied to individual activities on start, during the time between and at finish, help the model to carry out of tasks and the occurrence of breakdowns takes place in a manner that represented the existing crusher machine. After this, the entities would move forward to the conveyor to exit the system and this cycle would carried on until the specified run time of the model.

This enables the user to run the model for any duration of time and extract accurate readings via the use of implemented variables, rules, formulae, automated response system and the statistical analysis the *Witness Simulation* package provides. By following this process, the user was able to see exactly when the occurrence of breakdowns took place according to the research data gathered with the help of expert knowledge.

6.3 Bayesian Simulation Model

The Bayesian model has all the additives of the base model and the *Mean Time Beween Failure* model except one very important aspect i.e. now stoppages would be disabled, as the MTBF for breakdowns is not under scrutiny but rather the influencing factors (parameters). These parameters would now decide when a breakdown should occur according to usage based on research data and expert knowledge.

For the ease of implication of the three parameters into witness, all three parameters are now based on Life**, "**Used"- and "Remaining", this represents each parameters usage as can be seen in figure 6-12. This usage rate is also represented by "life span", which is the estimated life span/duration a parameter resides within an activity until they require further action. This life span has been changed to a probability percentage of 100, where 100 represents maximum usage and end of life.

Figure 6 Life consumption & average probability of parameters

Hence, the model for ease of not only implication but also logical understanding has two variables per parameter, used and remaining. A time/usage is being consumed, elapsed time will increase and the remaining time will decrease simply because the lifespan of the 3 parameters are coming to an end or being consumed as time passes.

The formula for variables **"**Used*"* and "Remaining" has been applied via use of the dummy entity "Drill", the activity "Dummy" and the resource "operator". The modelled icons are shown in chapter 5, tables 3 and 4 that shows a graphic representation of the dummy entity, activity and resource used within the modelled system.

Figure 6 Dummy System applied within simulation model to aid programming

Figure 6 Parameter Percentage programming and detailing of dummy entity

In order to achieve the classification of variables shown in figure 6.12, figure 6.14 shows the implementation procedure of the formula where the "IF I state" rule is used within the Actions on Create for the entity Drill.

The I state programming function normally returns an integer value, containing the current state number of the specified element, however, on this occasion it has been applied to the resource Operator as can be seen in figure 6.14. Hence, you can use the I state function to return the state number of a specified resource. The state number identifies the current states of the resources i.e. whether the resource is "Off-Shift (0), Free (1) or Busy (2)", which are all represented by the use of number as indicated. The formula used in figure 13 uses 0 indicating the operator (resource) is off shift.

Therefore, the first line of the formula represents “if the operator is off shift”, after which the software will move forward to the next line i.e. Drill head (1) representing “Drill head USED”, equals itself plus 100 which represents the percentage, divided by the life span of the parameter which in this case is 10080 minutes. Hence, this 100 percent will be divided by the time resulting in a percentage.

Similarly, Drill head (2) the next figure down represents “Remaining”, after which (3) and (4) represent a whole percentage. The same applied for all 3 parameters however, the “Remaining” usage is simply done by extracted the “Used” usage rate, and the to derive a percentage, the figure are simply divided by 100 as can be seen in figure 6-15 which has been applied to the Dummy activities Actions on Input.

Figure 6 Parameter Percentage programming and detailing of dummy activity

This formula is based on the resource (operator) being *Always Available* and the entity Drill having an Inter Arrival Time of 1 minutes. This enables firstly that, as soon as the model has started running, the resource is available regardless of circumstance, and secondly that the entity Drill arrives every single minute without miss. This combined with the formula ensures that, as entity Drill arrives every minute the exact same percentage is added every minute to the variable Drill head used until 100 percent is reached. The same applies to the remaining parameters as can be seen in the formula presented in figure 6-14.

The parameters do require attention as they reach maximum life span at 100 percent and need adhering to; however, if all the parameters almost reach the end of the life span simultaneously, this combined as a whole can easily cause disruptions as more than one parameter has nearly reached the maximum usage. This is based on historical and expert opinion of the machinery [9].

Therefore, a further counter (variable) exists, where; all three parameters have been implemented into a single probability that represents the machine as a whole. This counter takes into consideration all three parameters and derives an average in order to extract the best result as seen in figure 6-12, Average *Probability*. This is simply done by adding the 3 *Remaining* usages of the parameters and then dividing them by 300 and multiplying 100 to give an overall average percentage ratio of Working or Failure as shown in figure 6.16. This also has been implemented within the DUMMY activity, where WORKING (1) represents the total i.e. Drill Head (2) + Dusting (2) + Lubrication (2). WORKING (2) represents the working rate i.e. The total (working (2)), divided by 300 (collective ratio of parameters) and multiplied by 100. WORKING (3) represents the Failure rate i.e. 100 subtracted by the Working rate. WORKING (4) and (5) display a percentage ratio of the working and failure rate. All the formulas are shown in figure 6-15. All the working ratios are within the model are shown in Table 6-1

Figure 6 Programming the average probability formula into dummy activity

Table 6. Average probability working ratios representation in simulation model

All the procedures so far aided the modelling, where all the needed variables for “USED and REMAING” were running to its full capacity, however, there existed a slight error in programming. The error was significant in nature as it affected the entire system of results but very small in programming terms. This error meant that all USAGE rates would surpass the 100 percent threshold after maximum consumption as the Drill entity arrived every minute, which in turn resulted in inaccurate readings. This error was rectified by the simple implementation of the formula shown in figure 6-17 at specific locations.

This meant that as soon as entities leave their designated activities, the USAGE rate will return back to ZERO indicating that the full life span has been restored. The formula had to be inputted in all the setups actions on finish as can be seen in figure 6-17 for all 3 parameters. This returns the value back to zero as soon as entities exited the activities.

Figure 6 Restoring the Life Span of parameters via rule

All the modelling was now in an accurate state and the next step was to implement the occurrence of breakdowns according to the failure rate according to the research data of the parameters [9]. This meant that, anything above the 90% failure rate threshold consensus reached by the experts as the point of deterioration [9] on the overall average as highlighted could be classed as a failure. As three parameters combined reach near their maximum potential usage rate then the rate of failure increases dramatically whereas in the case of a single parameter, it can consume its entire life after which the tasks can be carried out or the parameter can be changed.

Modelling the breakdown was also done via the use of the DUMMY activity as shown in figure 6-18 where the formula's has to be applied. Where its states, "IF WORKING(3)", which is the average probability for failure (failure rate), is equal to or above 90 represented by " > = 90", then the 3 activities that represent the crusher machine as a whole should breakdown, represented by BREAKDWN (Crusher), BREAKDWN (Crusher01) and BREAKDWN (Crusher02). However, " IF Lubrication (1) < 90 OR Dusting (1) < 90 OR Drill Head (1) < 90", implies that, if any of the parameters usage is actually below the 90 usage rate, the activities should resume, as shown below in the formula. However, "IF" all three parameters have actually surpassed the usage threshold of 90 then the breakdown should occur. This is based on the data gathered and expert knowledge in order to be a very good representation of the actual system, which is mostly subjective information [9].

Figure 6 Applying breakdown formula for crusher machine

After completing the breakdown implementation the model was ready for further testing and evaluation, this enabled the user to see when breakdowns occurred according to the average probabilities of the influencing factors. Comparisons could now be made with the MTBF model to see if the breakdowns which occurred, had any relation to the usage of existing parameters.

The next step was to implement the *Chain Rule* that is used by the Bayesian network to formulate the probability of failure within the model developed. The Bayesian network is only able to produce results of failure on a static basis i.e. numbers that represent the condition of the parameters have to be inputted into the *Conditional Probability Table* (CPT) after which results can be extracted. Different conditions represented by numbers have to be applied and hence changing the CPT for results is an on-going process.

The Witness Simulation model on the other hand will not require the input of any data. All the conditions of the parameters have now been changed to two simple variables i.e. *USED* and *REMAINING*. The CPT enables the *Chain Rule* to extract variables and calculate the probability of failure. This *Chain Rule* will now be implemented within the model that will extract conditions of parameters on an ongoing process abolishing the need to input any data. This will produce a sophisticated dynamic approach, the model will show an array of different probabilities of failure based on the condition of parameters as usage rates increase, and time passes.

In order to understand this process thoroughly, it is very important to understand the *Bayesian Network Modelling* process as it was simply highlighted in chapter 3 (3.7.2). The Bayesian process will now be presented to develop key understanding of the Chain Rule and the use of variables.

6.4 Bayesian Network Modelling Using Hugin

6.4.1 Introduction

Bayesian network modelling is a mathematical technique used to model uncertainty in a chosen area or a system. It can help identify and highlight links between variables [62]. The recognition of important variables as well as consideration of other influencing factors that seem to exist within the system is integral to the Bayesian approach. Bayesian network modelling is a mathematical formula that calculates conditional and marginal probabilities of a random event at any given time [63].

Witness Simulation has much to offer any organisation. The role of simulation is to evaluate alternatives that either support strategic initiatives, or support better performance at operational and tactical levels. Simulation provides information needed to make these types of decisions. The simulation approach supports multiple analyses by allowing rapid changes to the models logic and data, and is capable of handling large, complex systems such as a manufacturing facility [64].

The model developed aims to reduce the effects of breakdowns that occur within the crusher machine using the Bayesian network modelling and Witness Simulation combined, in order to replicate the machine and the parameters that exist. The development of the model will result in a new approach in calculating the likeliness of a failure occurrence.

6.4.2 Overview

Bayesian network modelling relies on Bayes' theorem as a rule of inference [22, 63,132] i. e. observations and data are used to update uncertainty of any parameter or node in a Bayesian model. This relates to the conditional and marginal probabilities of two random events, which calculates the posterior probabilities given observations of the two events. If events A and B are considered, where event A is the influenced node and event B is the influencing node, Bayes' theorem [68,133] states:

$$PAB= PBAP(A)P(B)$$

This theorem forms the basis of Bayesian network modelling. A Bayesian network is a directed acyclic graph (DAG) that encodes a conditional probability distribution (CPD) at the nodes based on the arcs received. The nodes can represent any kind of variable or event. A Bayesian network is therefore a DAG encoded with a CPD.A, an arc goes from one node to another node making a connection in one direction only (acyclic) as shown in figure 6.19. A node is generally drawn as an oval that represents the variable or event. The arc is generally a straight line with an arrow head illustrating the direction from the source node, often called the parent node, to the other node (target), often called the child node, representing the probabilistic dependence between the two variables [65, 66, 134].

6.4.3 Methodology

The methodology has been highlighted in chapter 3, however it will describe in further detail in the following sections.

1. Establishing relevant and accurate information
2. Establishing nodes with dependencies

One of the advantages of Bayesian network modelling is its flexibility in enabling new nodes to be added to an existing model. It allows existing information previously added to be updated as new information is gathered [67, 69, and 70]. An example of Bayesian network is shown in figure 6.19 which represents the crusher machine and the parameters.

Figure 6 Bayesian Network Modelling of a Crusher Machine and Parameters

The crusher machine's critical parameters that lead to machine failure are the drill head, dusting and lubrication. The drill head has to be changed once every 7 days due to the amount of time spent crushing raw materials that cause wear and tear. Too much wear and tear of the drill head means the quality of crushed raw materials are affected, and at times, they can take much longer to process. Due to the drill head breaking raw materials and crushing, much dust or small particles and fragments of rock gather in different areas of the machine and hence has to be cleaned in order to prevent failures i.e. dusting. Lastly, the machine must stay lubricated in order to work affectively because the lack thereof will cause failures to occur i.e. Lubrication. Figure 19 shows the three parameters with arrows pointing downwards to the crusher indicating that they influence the crusher. Further each node has two states i.e. ‘Used’ and ‘Remaining’ that can be seen in figures 6-20, 6-21 and 6-22. This example models the dependencies between the above parameters and the crusher.

3. Establishing of CPT (Conditional Probability Table)

A Bayesian network can visually represent the relationship between various nodes or event (qualitative representation), or it can quantitatively represent each node through a conditional probability table (CPT) as can be seen below in figures 6-23 [69,70and135].Further, each parameters states are given a probability i.e. figure 6-20 shows the drill head has 70% used and 30% remaining, the same system is followed for figure 6-21 and 6-22. The given probabilities can be based on historical data that has been gathered over time, research or expert knowledge/opinion.

Therefore, the probability of the crusher machine failing or working is dependent or conditional on the existing parameters. This can be seen in figure 6-23 the conditional probability table for the crusher machine.

Figure 6 Applying percentages (state) to Drill Head

Figure 6 Applying percentages (state) to Dusting

Figure 6 Applying percentages (state) to Lubrication

Figure 6.23 shows the probabilities of breakdown for the crusher machine based on the parameters, where at one end if all 3 parameters are ‘remaining’, the probability of ‘working’ can be 100%, whereas on the other side of the table if all 3 parameters are ‘used’ the probability of ‘failure’ can be 100%.

Figure 6 Crusher Machine and existing Parameters conditional probability tables

4. Normalised Probability

Probability values have to be between 0 and 100. All the values however are automatically normalised by using the Hugin Software that is used to develop the CPT tables and further probabilities as shown throughout the building of the model.

5. Propagate Evidence

Fixing of nodes whilst other variables change accordingly enables propagation. Based on a mixture of historical data and expert knowledge, three CPT Tables were created where the nodes life consumption and usage were fixed i.e. the failure of the Crusher was based on fixed dependency values.

6 Model Validation

In this example, the node crusher machine is dependent or conditional on the 3 parameters that exist and hence have influencing effects on the generated probability. In order to calculate the probability of the 'failure' of the crusher machine the Chain Rule (6.1) must be applied.

The nodes Drill Head, Lubrication and Dusting can be termed 'A', 'B' and 'C' respectively, and the Crusher machine termed 'C'. The term 'CF' can represent the state Crusher Failure.

P(CF)i=13j=13k=13P(CFAiBjCk)P(Ai)

P(Bj)P(ACk) **(6.2) [71]**

Therefore,

P (Crusher Failure) =

P (Drill Head ‘Used’) x (Lubrication ‘Used’) x (Dusting ‘Used’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Used’) x (Lubrication ‘Used’) x (Dusting ‘Remaining’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Used’) x (Lubrication ‘Remaining’) x (Dusting ‘Used’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Used’) x (Lubrication ‘Remaining’) x (Dusting ‘Remaining’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Remaining’) x (Lubrication ‘Used’) x (Dusting ‘Used’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Remaining’) x (Lubrication ‘Used’) x (Dusting ‘Remaining’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Remaining’) x (Lubrication ‘Remaining’) x (Dusting ‘Used’) x P (Crusher ‘Failure’) +

P (Drill Head ‘Remaining’) x (Lubrication ‘Remaining’) x (Dusting ‘Remaining’) x P (Crusher ‘Failure’)

This rule can be further simplified by looking at figure 6-24 (CPT for crusher machine), where the arrows indicate how the equation is used and how variable are selected to develop probability. It works from the right side using all the conditions selectively through to the left enabling the development of the probability.

Figure 6 CPT for crusher machine based on parameters

Therefore, P (Crusher Failure) =

(0.7 x 0.5 x 0.6 x 1) + (0.7 x 0.5 x 0.4 x 0.75) + (0.7 x 0.5 x 0.6 x 0.625) + (0.7 x 0.5 x 0.4 x 0.5) +

(0.3 x 0.5 x 0.6 x 0.375) + (0.3 x 0.5 x 0.4 x 0.25) + (0.3 x 0.5 x 0.6 x 0.125) + (0.3 x 0.5 x 0.4 x 0.0)

= 0.57625 or 57.625% probability.

Given the above equation, it can be seen when compared to the actual example model of the crusher machine nodes and dependencies, the outcome or probability is the same. This data has been implemented and modelled using Hugin software with the above states, results are shown in figure 6-25.

Figure 6 CPT results for Drill Head, Dusting, Lubrication and Crusher

From the example it can be seen, given the above probabilities of the 3 parameters, that the crusher machine has a 57.625% probability of failing. A crucial advantage of the Bayesian approach is that it allows updated information to be considered in order to develop revised probabilities.

Consider another example. The ‘Drill Head’ has now been fully used at 100%, this indicating that maximum usage has been made and a change is required. This should increase the probabilities of failure for the Drill Head that should result in changes to the probability of failure for the crusher machine. This can be seen in figure 6-26, where the drill head has been used 100% has resulted in a dramatic increase for the failure of the Crusher machine i.e. probability of failure is now 73.75%.

A single parameter being used 100% does not equal to a failure of the machine but rather an indication that the parameter needs attention. However if all three parameters consumption is 100% this would without doubt lead to failure of the machine according to the Bayesian approach aided by expert knowledge.

Figure 6 Drill Head usage 100% results in increase in failure probability

Similarly, as explained, the *Chain Rule* that has been developed is to validate the probability, this same rule has also been implemented into the Witness Simulation i.e. Equation 2 has been applied to the simulation to work out a live dynamic probability as the model is simulated.

The *Chain Rule’s* equation has now been changed into a witness simulation rule via the use of variables. These variables represent the rules exactly as it is in the chain rule and similarly makes use of the CPT’s figures to work out a probability for failure as displayed within the witness simulation model.

The rule in table 4 is the exact same as the rule explained and shown , it consists of 8 segregated rules or equations (variables) that are added together to show the probability as shown in the CPT figure 6-24.

There are 8 different variables from the CPT table that have been used in order to attain the accurate results i.e. figure 6-24 shows the '*Failure'* and '*Working'* rate that are dependent on parameter consumption. This can be seen below in the equation where the variable start at the failure rate of 100 and slowly starts to decrease in the same order as the CPT table in figure 6-24. Finally, all the 8 variables are added together to complete the probability of failure.

Table 6. Chain Rule Probability Formula

Variable1 = Drill Head (3) * Dusting (3) * Lubrication (3) * 100
Variable2 = Drill Head (3) * Dusting (4) * Lubrication (3) * 75
Variable3 = Drill Head (3) * Dusting (3) * Lubrication (4) * 62.5
Variable4 = Drill Head (3) * Dusting (4) * Lubrication (4) * 50
Variable5 = Drill Head (4) * Dusting (3) * Lubrication (3) * 37.5
Variable6 = Drill Head (4) * Dusting (4) * Lubrication (3) * 25
Variable7 = Drill Head (4) * Dusting (3) * Lubrication (4) * 12.5
Variable8 = Drill Head (4) * Dusting (4) * Lubrication (4) * 0.0

Probability = Variable1 + Variable2 + Variable3 + Variable4 + Variable5 + Variable6 + Variable7 + Variable8

This chain rule is represented by the eight variables within the simulation as can be seen in figure 6- 27, where the probability of failure is visible as is the different variables based on equation 2.

Figure 6 The Chain Rule Variables and Probability in simulation model

Similarly, the formula in table 6.2 is inputted into the dummy activity as can be seen in figure 6-28, where all 8 different variables are clearly visible with the overall probability displayed at the very bottom.

Hence, as the model is running, the simulation model determines the probability according to the Bayesian approach in order to develop a dynamic approach. The need for continuous implementation of new data is no longer required, as the fundamental process of the CPT has now been trialled and tested to suit the needs of the model and research required with the help of expert knowledge.

Figure 6 Chain Rule Programming Representation in simulation model

The breakdowns occurrence will now be totally dependent upon the probability of failure with the help of expert knowledge as it takes into account all influencing factors and abolishes the occurrence due to unknown reasons as well as the MTBF. Breakdowns will only occur now when the parameters simultaneously combined together surpass the 90% probability of failure.

The 90% failure rate has been chosen with the consultation of expert knowledge, this was then transferred into the Hugin model to validate that all parameters surpass the 90% threshold usage rate simultaneously. This is shown in figure 6- 29, where all parameters actually have to consume 92.5% usage rate in order for a 90% failure rate to occur.

Figure 6 Hugin Failure Rate based on all parameters consuming 92.5%

In order to demonstrate the methodology of the Bayesian process and added value of individual parameters, a case study of a factory producing carbon black in the UK is shown. This case study is to validate the process used in developing the conditional probability tables that have been used within the model construction and aided understanding throughout the research.

6.5 Advantages of Bayesian network Modelling

- As nodes are modelled by means of probabilistic distributions, risk and uncertainty can be predicted far more accurately than in models where only the mean values are taken into consideration [94]. The delay time analysis carried out in this case and the MTBF model are both entirely based on statistical averages that consider the mean values with high regard. This probabilistic representation makes Bayesian network modelling a more appropriate tool for modelling machine breakdown occurrences, since it can deal with uncertainty more precisely [95, 96, 97, 98; 99, 100].and also has the following benefits:-

- As numeric values are attached to the relationship between the existing variables, the probability of a particular hypothesis can be automatically computed [101, 102].

- The probability distribution of a node given its parents is obtained and probability conversely distribution of a parent node given its child nodes can be derived [103, 94], which allows one to know the effects given the causes and the causes given the effects, and as such they are used as inferential models (104, 98).

- Expert opinions and knowledge are the key to when modelling a given problem, as they can guide the model to focus on important aspects, or the model to find inconsistencies or differences with the established data [105, 106, and 100]. However, this procedure has to be done properly in order to avoid errors or bias in the model. Bayesian network models are able to incorporate expert knowledge as the relations between the variables can be visualised easily through the graphical representation of the network, and so they can be modified by the experts or under expert guidance by adding or removing variables and links in the graph. This makes them easier to understand and visualise by the end users [95, 96, 97, and 105].

- Bayesian network models are able to model complex systems with any number of variables in a quick and efficient way depending on circumstances [107, 94]. If an exact solution is difficult to get to, there are algorithms available that can achieve an approximate solution i.e. using simulation techniques or deterministic approximation methods [107, 108].
- Bayesian network models are able to manage missing values in input data and perform the proper predictions with the model built from them [109, 110, 111, and 112].

However, many authors also mention some limitations to the system and approach;

- The building process of the network and the parameter estimation requires more data if the accuracy in the estimations and in the network is to be maintained as the number of variables increases [113,101].
- The main problem is that data available, are continuous or hybrid, and even though Bayesian network models can manage them, the limitations are too restrictive [114, 115and 94].
- Time series can be modelled as Dynamic Bayesian network models [119] as the links in the networks may be considered as the effect of time over the variables. However their complexity makes medium size models usually nonflexible as the number of variables involved is greater than the static models [120].

- Fuzzy models [121, 122, and 123] are a different way to express uncertainty in a model, more related to ambiguity or fuzzy events. Bayesian network models are useful tools to deal with probabilistic theory, but they are also able to handle these fuzzy models, using Credal networks [124, 125, 126], in which the relation between two variables is expressed in terms of sets of probability distributions. However, these models are not yet incorporated to the usual commercial Bayesian Network Modelling software.

Case study –The use of Bayesian network modelling for maintenance planning in a manufacturing industry

The case study uses the delay-time analysis in order to extract the failure rate of parameters after which the Bayesian network modelling is used to improve the accuracy of the parameter failure rate taking into consideration all influencing factors.

The key parameter under scrutiny in this case study is the failure of a filter bag that can have several factors that contribute to the failure. The age of the filter bag is of most importance, the nearer the filter bag is to the end of its life, the higher the probability of failures.

Filter bag temperature is crucial, if the temperature of the filter bag is too low, then deterioration of the bag can take place dramatically due to condensation from sulphur. High temperature spikes in the bag can easily result in the burning of the bag, this failure probability further increases as the age of the filter bag increases. Operator competence is also considered in this case study, however, it is not given the same influencing value due to the increased levels of automation processes. The final influencing factor is general equipment failure. The process of a filter bag is very simply and can be categorised as follows:

- The bag is filled with carbon black which increases the pressure.
- The bag is then decompressed thus crushing the bag slightly, which releases the carbon black from the bag and into a loading compartment beneath the bag.
- The bag is then refilled with carbon black thus replicating the process all over again.

i.e. establish nodes with dependencies

From the case study, the nodes that have been categorised based on influencing the failure of the filter bag are as follows:

a) Operating temperature
b) Age of filter bag
c) Competence of operator
d) Equipment failure

Figure 6.30 illustrates the nodes which may contribute to the failure of a filter bag.

Figure 6 Nodes of the failure of a filter bag.

Each node has an influence on the failure of a filter bag, it is important to distinguish the value of each node. For example, the node `competence of operator' is regarded as having a lesser influencing effect in this case than that of 'operating temperature'. This is due to the 'operating temperature' being responsible for failure both directly and indirectly of a filter bag.

i. Create CPT (Conditional Probability Table) and prior probabilities for each node

The next step is to establish a CPT for each node. Information is gathered from historical data and from expert judgement. The CPT for each node is illustrated in figure 6.31.

Figure 6 CPT for each influencing node relating to 'failure of a filter bag'.

Figure 6.31 shows, each CPT has been populated, all the nodes represents the probability of the system over the last 12 months, given that it is commonly agreed as 1 failure / day in this analysis. The data available has illustrated that the system had overheated (failed) once over the 12 month period which, applying Equation 3, gives:

(6.)

Applying Equation 6.2 to this case study allows the use of failure data to become available as a probability for use in the Bayesian network model. Equation 3 accepts 1 failure per day, which will equate to 100% failure. Failures exceeding this figure would still be regarded as 100% failure as anything higher than 1 failure per day is regarded as unacceptable. All the nodes are established using the same logical premise in the case study which is used for `Operating temperature'.

The competence of the operators is set to 90% good, 5% average and 5% poor, this is due to the absence of operator error in filter bag failures. The node `age of filter bag' contains two states, `life elapsed' and `life remaining'. The state `life elapsed' describes the age of the filter bag as a percentage of the total life expectancy of the filter bag. The state `life remaining' describes the remaining life of the filter bag, again expressed as a percentage. In this case study the age of the filter bag is 33 days or 2.59% of `life elapsed' with 97.41% 'life remaining'. The age of the filter bag becomes a main additive to failure when combined with other influencing nodes, for example, high temperature spikes. Figure 6.32 illustrates the CPT of `Failure of a filter bag' based on all influencing factors.

Figure 6 CPT for 'Failure of a filter bag'.

It is clearly seen how quickly a Bayesian model can become complicated. In figure 6.32, it can be seen that the four influencing events are listed in the left vertical column: 'Operating temperature', 'Equipment failure', 'Age of filter bag' and 'Competence of operator', with the node 'Failure of a filter bag' being either 'Failure' or `Working'. The values for the CPT's are based generally on historical data but some aspects of the data has been examined and given probabilistic figures based on expert opinion, for example, the difference between 'Competence - Good' and 'Competence - average'.

Having established the CPT for each node, both 'parent' and 'child', a normalisation is required for each. Normalisation has been carried out in this case study by either simple calculation prior to inputting the probability data into the CPT or automatically from the (Hugin) software used. Propagation of evidence can now be carried out to examine differing scenarios given one or more varying pieces of evidence.

ii. Propagate evidence

The propagation of evidence examines several different scenarios and combinations of events taking place. Propagation serves to highlight a problematic area that may require closer scrutiny should a certain event take place. Taking into account all the probabilities, the failure probability of a filter bag is estimated to be 0.21%. Applying equation 3 to this failure probability makes it possible to transfer the failure probability to failure rate. A failure probability of 0.21% applied to equation 3 will then equate to a failure rate of 0.0021 failures/day or MTBF of 476 days. This is illustrated in figure 6.33.

Figure 6 Prior probability of `Failure of a filter bag'.

With the age of the filter bag remaining at 34 days, this evidence may be fixed in the model i.e. this parameter will not change given other changes in the model. Having fixed the age of the filter bag, a useful scenario to be tested can be to simulate a high temperature spikes illustrated in figure 6.34.

Figure 6.Probability of 'Failure of a filter bag' given a high temperature spike.

A high temperature spike increases the failure probability, this is the major influencing factor that can cause failure of a filter bag. A temperature spike occurrence when a filter bag is approaching the end of its life expectancy increases the occurrence of failure due to an increase in brittleness of the bag, illustrated in figure 6.35

Figure 6 Probability of 'Failure of a filter bag' given both a high temperature spike and aged filter bag.

A high temperature spike together with the age of the filter hag (100%), the probability of failure of a filter bag rises to 20.76%. Similarly, if the competence of operator is poor (100%) it aids further increases to the probability of failure illustrated in figure 6.36 where three parameters are at risk.

Figure 6 Probability of 'Failure of a filter bag' given a high temperature spike and aged filter bag together with 'poor' competence of operator.

The increase in probability of failure of a filter bag illustrates a significant increase from 20.75% to 30.01%. Further, Incorporation of the final influencing factor 'equipment failure' illustrates further increase for failure of a filter bag, moving from 30.01% to 32% illustrated in figure 6.37.

Figure 6 Probability of 'Failure of a filter bag' given the probability of all influencing factors taking place.

The final illustration shows the effects of failure of a filter bag ('Failure' 100%) on the influencing parameters. The model showing failure of a filter bag is illustrated in figure 6.38.

Figure 6 Model illustrating when the failure of a filter bag takes place.

This illustration has given an insight into the possible causes that may be responsible for the failure of a filter bag. Here the major influencing factors are that of the `operating temperature - high' moving from 0.27% to 20.77%, `equipment failure' increasing from 0.54% to 6.2% and `competence of operator' moving from 90% `good' to 23.59% with `average' and `poor' increasing significantly from 5% to 25.9% and 50.51% respectively.

iii. Validation of model

A sensitivity analysis has been carried out in the case study in order to give a partial validation of the model. The model had to satisfy the three axioms described in section 3.7 of the case study. The illustrations shown of increasing each influencing node satisfies the axioms stated in section 3.7 of the case study, thus giving a partial validation to the model.

6.6 Discussion

This case study uses the Bayesian network modelling approach to establish the failure of a filter bag for use with and in comparison to the delay-time analysis with a greater accuracy than that obtained using the traditional means i.e. statistical averages taken over a given period of time.

The aim of this case study is firstly, to show the use of the Bayesian network modelling and the processes involved. This has been followed in this thesis and thereafter how the Bayesian network modelling can be used to validate and enhance the results extracted from statistical averages.

The parameters required to carry out the study using the delay time analysis that come mainly from and has been previously established using historical data calculated using statistical averages based on purely objective means. This method however cannot be adapted to the ever-changing influences responsible for failures and their effects on equipment or components. The Bayesian network modelling was therefore used to counteract this area of concern.

The Bayesian model in this case study allows relevant information to be considered that influence the failure of a filter bag. The inclusion of these influencing factors has given a greater understanding to the parameter failure rate, resulting in a greater confidence in the overall results of the delay-time analysis.

It has been demonstrated in this case study that the optimal inspection interval has been refined and improved using Bayesian network modelling to establish failure rate. The re-evaluation of the parameter failure rate using the Bayesian approach has reduced the optimum inspection interval.

6.7 Conclusion

This case study has served to give a better understanding and confidence to the parameter failure rate. It has not only given an opportunity to increase the accuracy in a modular way, but also given an insight into the likely causes of failure.

This chapter has demonstrated the use of applying Bayesian network modelling to provide an improved and accurate method of establishing the occurrence of failure. Although the inspection interval has been optimised, greater confidence can now be given to the results of this study given the inclusion of several consequential factors relating to failure.

The MTBF model is based on the gathering of objective information from historical data and statistical averages, similar if not the same to the delay time analysis, hence is easily categorised as a traditional means as the occurrence of breakdown is solely based on statistical averages. This information was applied to a simulation model to establish breakdown occurrences. The same historic data as well as expert judgement has been used for Bayesian model building which not only takes into account statistical averages but all influencing factors with expert opinions.

Bayesian model developed based on the influencing parameters and their added value results in a decrease in the number of breakdown occurrences when compared to the MTBF model. Further, the results of the parameter usage rates can be compared to see the condition of individual parameters when breakdowns occur according to other techniques.

This chapter has highlighted the extent of the Mean Time Between Failure (MTBF) model, how it represents an accurate representation of the existing machine based on historical data and statistical averages. The Mean Time Between Failure (MTBF) concept has been explained in terms of simulation model building and the all elements within the modelled system has been discussed with reasoning bringing to light the accuracy of the model compared to the real data gathered. The Bayesian network modelling has been introduced fully after which, the application of the Bayesian model to the simulation model is explained in order to understand the reasoning and knowhow of the implications to the simulation model. This took into account the implementation of the chain rule into the simulation model via use of different variables and formulae, which was validated and verified by the Hugin software that is actually used in order to generate the probability of failure. The Bayesian model proved to be an accurate representation taking into account the existing parameters, their usage rates and the failure probability developed that had been further validated by expert knowledge and opinion. The help of a case study that uses the Bayesian network modelling technique to improve their results and understanding aided this.

The purposes of identifying two separate models was firstly, to develop an accurate representation of existing machine, and thereafter develop the model further to implement the Bayesian approach in order that comparisons can be made as to see the best fit, based on actual data gathered and expert knowledge and opinions. This also enabled the development of a more informed understanding on how both models work, what they take into consideration, hence generating two completely separate results by the use of Witness simulation.

6.8 Summary

This chapter gives a deeper insight into the Mean Time Between Failure (MTBF) model and where the values have been derived from giving an insight into the historical data available. Bayesian network modelling is explained and the Bayesian application to the simulation model is highlighted and discussed. The different techniques used to develop those models and to understand the purpose of different elements and how certain equations have been implemented with reasoning based on replication of existing systems within the system to derive the best results for an accurate comparison to be made and analysis to be carried out. A case study has been used in order to validate the Bayesian process and enhance understanding and value.

Chapter 7

Data Collection

7.1 Introduction

This chapter highlights how data is collated with regards to the specific problems described in chapter 2 and the literature review in chapter 3, in order to develop a greater understanding of the analysis of the data. Further discussions include how and where the data has been used to derive the best results and represent an accurate system by means of verification and validation.

7.2 Data collection

Data sources include databases, manual records, and automatic data collection systems, sampling studies, time studies and case studies. Unfortunately, much, if not all of the data needed is not readily available and when available, it is not of the desired quality and scope. In these circumstances, much effort and expense may be required to collect the data or extract it from existing collated data. After collecting vast amount of data, a further requisite may be to validate the data. Surprisingly, data extracted from computerised systems i.e. databases, may not be correct at times due to human error. In the case where the majority of the data collected happens to be in a different language, mistakes of misinterpretation can occur without realising [72, 73].

A great deal of effort was required to cleanse the data to ensure its accuracy. Continuous consultations with experts were critical to the entire project. On the encouraging side, this requisite was required during the research and the model building, and hence happened before the new system could be put forward to the management or actual operation. When data on an activity (machine) is available, if the data consists of random variability, i.e., variability for which no immediate cause is evident, the activity duration is usually modelled based on a statistical distribution.

The success and validity of any research mostly depends on the selection process of the research method that is used to collect, analyse, and interpret data. The selection process of the required research method should be controlled by the research objectives, and availability and type of the required data [76].

With some types of data depending on accuracy, the user may decide to use the actual data as input in the simulation model. This may be done at the organisations request because it is simply too difficult to represent the data as a statistical distribution. For example, the failure of the crusher machine is dependent on all parameters surpassing the 90% usage rate based on historical data and expert knowledge. In this and similar situations, it has been decided to use estimated usage rates to drive models. The 90% threshold for individual parameters was first chosen based on normal wear and tear, consultations with experts revealed that the initial deterioration or initial tell-tale sign would start after a 90% usage rate of parameters. Hence, 90% had been chosen and not 85% or 89% under the guidance of experts in the field who deemed it to be an accurate representation based on their use of the existing parameters.

With this in mind, along with the literature review undertaken in chapter 3 and highlighted problems in chapter 2, data was gathered with regards to the crusher machine. The areas of research included the existing parameters, the tasks, inspection, breakdowns and the overall maintenance that must be adhered to. All the information gathered was aided by expert knowledge and opinions. This enabled a balanced approach of both objective and subjective data.

7.3 Data analysis

Data analysis in qualitative research involves preparing the data for analysis, conducting different analyses, moving deeper into understanding the data, representing the data, and making a global interpretation of the data [72, 73, 74]. Several generic processes are described in the literature to convey the overall activities of qualitative data analysis for example:

- Organise and prepare the data for analysis

- Read through all data

- Begin detailed analysis

- Use a coding process to generate a detailed description of topics and subtopics

- The final step in data analysis involves making an interpretation of the data

The relevant data collected included (among others):the types of machines, products, parameters, operations, tasks and sequences of operations for each product, the number and type of machines required and available for each product and operation, actual production time, machine down time, inspections down times, and preventive or corrective maintenance times, reasons for rejection of products.

Data collection was conducted by using the following methods:

- Field research was integral in taking data during actual operation time
- Discussion with engineers, technicians and responsible personnel
- On-going consultation with experts on the field
- The use of previous records and documents (historical data)

Modelling the various researched operations and simulating them establishes a relationship between the actual and expected performances in order to make a comparison and suggests changes that could be made to improve the productivity of the machine in the use under consideration. For example, the crusher machine could not be represented by a single activity within the model as it did not meet the needs of the existing parameters i.e. the three parameters were required to enter and exit the same activity at different durations which was not possible.

The field research enabled the gathering of the following data based on observation and consultation:

- The overall condition of the machine
- The purpose of the machine
- Maintenance strategy for the machine which included preventive and corrective maintenance
- The duration the machine is active on a daily basis
- The number of hours the machine was classed as unavailable due to breakdown occurrences.
- The domino effect that a failure will have on production.
- The existing influencing factors of the machine
- The reason for machines breaking down
- The specification of the Drill Head that requires changing
- The time required to change the Drill Head

- The job specification of operators that carry out the tasks of Dusting and Lubricating
- The time required to carry out jobs on the machine
- The data collection method used to register all disruptions

All the above data was used to develop the simulation models with much consultation on a regular basis from the base model through to the Bayesian Model.

The developments of the simulation models involve specific steps in order for the simulation to be successful regardless of the type of problem and the objective of the study. The process by which the model building is done should remain constant. The following highlights the basic steps in the simulation process [75]:

1. Problem Definition
2. Project Planning
3. System Definition
4. Model Formulation
5. Input Data Collection & Analysis
6. Model Translation
7. Verification & Validation

8. Experimentation & Analysis

9. Documentation & Implementation

7.4 Developing a Valid and Credible Model

Important techniques and processes are followed to develop a valid and credible model in order for the model to be considered as a true representation and hence used in the decision making process by the organisation or management.

There consist an array of diagrams, descriptions, procedures and techniques that outline the key processes in the use of simulation and research thereof. Numerous authors have written about the process of simulation modelling including Hoover and Perry (1989) [77], Law and Kelton (2000)[78], and Robinson (2004) [73]. Each has their own preferential way of explaining how to develop a simulation model for best fit. A thorough analysis reveals vast similarities, outlining a set of processes that must be performed.

The following are important processes for deciding the appropriate level of model detail which can be difficult when modelling a complex system, for validating a simulation model, and for developing a model with high credibility.

- State definitively the issues to be addressed and the performance measures for evaluating a system design at the beginning of the study.

- Collect information on the system layout and operating procedures based on conversations with managers, operators and experts for each part of the system.
- Define all information and data summaries in an assumptions document which becomes the major documentation for the model.
- Interact with the manager on a regular basis to make sure that the correct problem is being solved and to increase model credibility.
- Simulate the existing manufacturing system and compare model performance measures i.e. throughput and average time in system, to the comparable measures from the actual system.

7.5 Model Verification

Whenever a simulation model is being built, it is necessary to check each step of the model as it progresses before moving forward to the next step. This can be classed as verification. Verification is the practice of ensuring that the model behaves as required, usually by debugging or through animation. Verification is necessary but not sufficient alone for validation as the model may be verified but not valid [79- 80].

There can be an array of verification processes, some are listed as follows:

- Have the programming (formulas and rules) checked by someone other than the programmer.
- Development of flow a chart which includes each logically possible action
- Follow the model logically for each action and each event type

- Closely examine the model output for reasonableness
- Have the Witness Simulation print the input and output parameters at the end of the simulation, to be sure that these parameter values have not been changed accidentally.
- Make the computer code as self-documenting as possible.

One should also give a precise definition of every variable that should be used and a general description of the purpose of each major section of code should be defined. This is a basic process a programmer would follow when debugging a computer program.

In the process model verification, an expert on Witness Simulation and lecturer on this subject has checked the model using a number of different techniques, to verify that the running model agrees with the assumptions, research and consultation documents. This is more than debugging in the programming sense. All model outputs should make sense and be reasonable over a range of the input parameters. Numerous techniques should be applied, including but not limited to:

- Stress testing, testing with a wide range of parameters and different random numbers.
- A thorough review of all model inputs and outputs, not just the primary measures of performance, but numerous secondary measures.
- Using the software's debugger, statistical analysis, animation and any other tools provided.

- Using selective traces, especially for complex portions of the logic.

A valuable attitude to take is the one of a true scientist i.e. make a hypothesis e.g. the model is correct. Second, try to prove the hypothesis to be incorrect. However, if after thoroughly trying, you do not have any evidence of a faulty model or system within the model, then conclude that the model is verified. From a scientific perspective, the best that can be achieved is a cautious verification.

Future tests or a change in conditions or data may identify a problem with the model requiring changes. There exist endless number of potential tests that could be carried out to test a model's validity, however, in practice; we have the time for only a certain number of them. Therefore the best we can achieve is a "failure to reject" the hypothesis of a correct or valid model.

7.6 Model Validation

Model validation involves the experts. Once the simulation analyst is convinced that the model is accurate and verified, the analyst should conduct a thorough model review with the experts or management [80]. It is important to have all members present who may have an interest in the model, and who expect the model to answer their questions and more importantly raise further questions.

Numerous techniques, similar to those used during verification, may be used during model validation, including

- Use of animations and other visual displays to communicate model assumptions,
- Output measures of performance for a model configuration representing an existing system or an initial design, so that experts may judge model accuracy.

If sufficient data has been collected on the actual system that matches one of the model's possible configurations, more formal tests may be conducted comparing the real system to the model.

Validation can be carried out using statistical averages developed by the simulation package compared with real data gathered from the research and experts. In terms of the crusher machine and existing parameters, all data entered has to replicate actual system which can be seen in chapter 6. In modelled systems, the discussions of the element times are prescribed accordingly including setups and breakdowns. For example life span of drill head is 7 days, in the simulation model this is translated into minutes giving a life span of 10080 minutes.

To validate the model, different models have been created with the aid of experts from the field, many consultations with regards to actual representation have been undertaken and the results discussed.

A stochastic analysis has also been carried out to validate the results further to see the existing variables of the system and enable greater understanding.

Figure 7 MTBF Breakdown Times displayed by the autonomous messages

Figure 7.1 shows the automated response system that collects data in terms of times, these times reflect the 3 tasks (parameters) being carried out and the occurrence of breakdowns according to the MTBF. The arrows in figure 7.1 indicate the time of occurrence for a breakdown in blue writing, the 1st breakdown happens to occur at 4692 minutes, which in fact is not anywhere near the programmed uniform time of 9000 to 9500 in minutes in which breakdowns should occur. This is simply because the simulation software halves the 1st breakdown time, hence the 1st breakdown can be overlooked. The following 4 breakdowns however occur within the given time as can be seen in table 7.1 and the duration for a breakdown is within the given time according to research.

Table 7. **MTBF Breakdown Times for crusher machine based on historical data**

Breakdown number	**Breakdown time (minutes)**	**Time difference (minutes)**	**Breakdown duration**
1	4692	**4692**	
RESUME TIME	4995		**303**
2	14212	**9217**	
RESUME TIME	14460		**248**
3	23726	**9266**	
RESUME TIME	24051		**325**
4	33074	**9023**	
RESUME TIME	33395		**321**

5	42606	**9211**	
RESUME TIME	42935		**329**

All the breakdowns occur within the given time with the exception of the 1st breakdown as explained and the breakdown duration is within the given uniform time of 240-360 minutes. This basically validates a working process as the breakdown durations are in working order and within the time frames. Table 7.1 is a table representation of figure 7.1 . Similarly, the tasks that are carried out are shown in figure 7.1 with the time of occurrences.

Figure 7 Applied Variable in simulation model to help Validation

Figure 7.2 validates the times taken to carry out tasks in relation to parameters indicated by *time taken*; these time frames are within the given duration needed to carry out the tasks prescribed. The simulation model also derives an average from the tasks and repair carried out which also indicate validity as the average times are within the researched time applied.

Table 7.2 shows the activity statistics derived from the simulation package, although only a few number can be seen, these are of great importance and represent key elements within the model. Table 7.2 will help clarify and validate further implications within the model as follows:

Within Table 7.2, there are 5 main variables of interest indicated with the help of arrows and the 4 main activities are listed clearly. The activities which combine together represent the crusher machine can firstly be seen to be *Free* zero period of time, this indicates and validates that the machines is working on a continuous basis throughout the course of model running time. On the other hand the DUMMY activity can be seen to be free for 100% of the time. This basically validates that the DUMMY activity is in fact an activity which holds no direct relationship to the other activities.

The *Busy* percentage shows similarly durations of time with a small variation of less than 0.5%.This raises the questions, as to where the remaining percentage of time has been spent. This remaining time is located within the setup time that has been implemented within the software to represent the time it takes to carry out tasks. The Crusher activity seems to have the highest percentage of setup time after which the other 2 activities follow. This is simply because the *Crusher* represents the activity where the *Drill Head* resides; *Crusher01* is where *Lubrication* resides and *Crusher02* where *Dusting* resides. They require A percentage of time based on how long their tasks take i.e. *Drill Head* has the longest time, after which the other 2 parameters.

The percentage of time the crusher activities have *stopped* is equal as it should be. This validates the fact that, when a breakdown does occur, all three activities breakdown together consuming the same amount of time.

Table 7. Witness Simulation Activity Statistics for crusher machine

The number of tasks carried out by the activities can be validated against figure 2 and seen to be correct. The DUMMY activity however has 43200 tasks carried out. This represents the entity *Drill*`s inter arrival time which enters the dummy activity every minute as the model is running. This validates the DUMMY activity and Drill entity to be in a working order as calculations are made on a minutely basis as the number of tasks is equal to the time the model has been run for i.e. 43200 minutes.

Figure 7.3 and 7.4 indicate the occurrence of a breakdown. For the purpose of simplicity and validation, breakdowns have been set when the average probability surpasses the 50% failure rate. This percentage of 50% is only used for the purpose of this example. It can be seen in figure 7.5 that shows the implementation of the breakdown rule to be in working order and validated. Similarly, in figure 7.4, represents a breakdown occurrence according to the probability generated by the Bayesian approach as can be seen. This has also been set to 50% to simplify the validity process. Furthermore, Figure 7.4 shows that the average probability is higher in percentage than the probability percentage indicating that the rules are separately implemented.

Figure 7 Model representation of Average Probability Failure based on 50%

Figure 7 Model representation of Probability Percentage Failure based on 50%

Further, if all the variables are added together manually, the results is equal to the probability as shown in Table 7.3, after which it is transferred into a percentage as shown in figure 7.4. This validates that the chain rule as implemented is in working order as the variables collated together display and produce accurate readings.

Table 7. Chain Rule Variables within simulation model

However, one can consider the variables further to certify the validity of the rule and the integration of the software and models developed. The Hugin Software [63] that uses the chain rule to derive and produce probabilities based on the conditions of parameters can also be used to validate the probability generated by the simulation package based on the programming implemented. Figure 7.5 illustrates an example of when the probability of failure is 57.625% based on specific consumption rates shown in figure 7.5. The used rate of each parameter is what generates such a particular failure rate i.e. Drill head 70% Used, Dusting 60% Used and Lubrication 50% used resulting in a failure probability of 57.625%.

Figure 7 CPT results for Drill Head, Dusting, Lubrication and Crusher.

Hence, one would expect or assume the simulation model to have the same consumption of usage for each of the parameters, however this is not the case i.e. figure 7.6 shows that Drill head is exactly the same at 70%, Dusting is 41% compared to 60% and Lubrication is 62% compared to 50%. This does not mean that the rules implemented or the witness model is wrong as the probability percentage acquired from these consumption rates that can be seen 57.64% which is almost exactly the same. One has to remember that the Bayesian approach although takes influencing factors into consideration only produces instant static results. This means that numbers or pieces of information have to be added and then calculation are made based on those figures.

Whereas the witness simulation works on a continuous flow, as the consumption rates change so do the probability of failure. In order to validate the model results these consumption rates can be entered into the Hugin Software for comparison.

Figure 7 Parameter usage rates based on Failure Rate 57.64

Therefore, the above consumption rates have now been applied to the Hugin Software respectively and can be seen in figure 7.7 where the failure rate has slightly increased from 57.645% to 57.84%, a very small deviation of 0.20%. This clearly shows that the Simulation Model developed is more than capable of developing a continuous probability for failure rate based on the consumption of parameters and validates the usage thereof.

Figure 7 Failure Rate based on parameter usage rate of figure 7.6

To validate the results of the simulation model further against the results of Bayesian network modelling, an array of different values of the variables were considered and tested, Table 7.4 shows some of the results. After the tests shown in Table 7.4, it was clear that the results were correct with a very small deviation; however, the consumption of the parameters was different.

This is simply a result of how the Hugin software works i.e. Table 7.4 shows the usage rate of each parameter, this usage rate is made up to test the system.

However, as highlighted above with the use of figure 7-6 and figure 7-7, when the probability of failure is shown in the witness model according to table 7.2, the usage of parameters are different to that which has been inputted.

However if these new rates of usage are applied back to the Hugin Software, the results are the same as shown in figure 7-7.

Table 7. Hugin and Witness Software Results for parameters based on failure

	Failure Ratios	Drill Head Usage	Dusting Usage	Lubrication Usage
Hugin Failure	57.63	70	60	50
Witness Failure	57.63	70	41	62
Hugin Failure	73.76	100	60	50
Witness Failure	73.78	78	71	81
Hugin Failure	91.38	90	90	100
Witness Failure	91.41	86	99	100
Hugin Failure	83.00	80	80	100
Witness Failure	83.04	82	86	92
Hugin Failure	74.87	70	70	100
Witness Failure	74.91	79	73	83

Table 7.4 shows very little variation in results of failure but however as highlighted previously, in some cases dramatic changes in parameter consumption rates can be apparent. This is simply because the witness simulation model works on a dynamic platform that changes the consumption rates continuously whilst the Hugin consumption have to be inputted by the user and does not change unless changed are made manually.

7.7 Summary

Chapter 7 highlights the data collection processes and analysis available and used in order to gain accurate results, after which the verification process is highlighted and the model is validated with the help of visual aids with reference to the actual models developed.

Chapter 8

Experimental Work, Results and Discussion

8.1 Introduction

This chapter discusses the results of the simulation models developed for the Crusher Machine. For experimental purposes, three models exist and will be discussed, results were obtained for the purpose of comparison and to develop a hypothesis as to which approach will be most suited. All the developed simulation models rely on the generation of random number streams, therefore the results generated by the models are dependent on distribution (i.e. uniform, negative exponential and triangle) used in the models. A stochastic analysis was carried out where fifty replications carried out enabled the effects of the distribution to be determined in order to increase the effect of confidence in the results.

The Witness Simulation package includes an experimentation module called the Witness *Scenario Manager* that was used to execute the different scenarios of the developed simulation models. This additional module can, in a short amount of time, produce the results of many replications just as the simulation software can compress time. The results are compared to determine which model would be the most effective in identifying the likelihood of a breakdown in the future and to enable management to make key decisions with regards to maintenance to reduce breakdown occurrences.

This chapter aims to show all the experiments carried out in order to develop a key understanding of the model requirements and building. From the experiments carried out on all the developed models, results will be extracted and analysed to indicate the most suitable model with reference to the research undertaken and objectives highlighted. Maintenance integration is also highlighted and the integration of such a tool is discussed.

8.2 Experimentation

The purpose of this phase is to meet initial project objectives: to evaluate and compare system performance and to gain insight into the system's dynamic behaviour particularly, into any problems or bottlenecks identified by the analysis.

The project plan developed during the preliminary stages and initiation provides the initial guidelines for a set of experiments. Simulation models are used to compare a large number of alternatives and to evaluate in greater detail a small number of recommended alternatives [84]. The assumptions, research and consultation document should include a description of expected model variations with reference to parameter inputs and outputs to be simulated, to represent the alternatives of interest.

In reality, initial model experiments often should raise new questions and may change the direction of the study [85, 86] i.e. initial experimentation may establish that a proposed new design or set of operating rules leads to major bottlenecks or other problems, and some major re-thinking of the system design is required. In each phase of the experimentation, actual model configurations should be guided by an experimental design that lays out the model parameters being varied, the range of each parameter, and the parameter combinations that make sense.

This study represented a similar problem at the initial stages of experimentation and design. The idea in mind was that a single activity within the simulation package should represent the crusher machine alone, however, this was not possible due to the application of the three existing parameters. As such, model design and layout had to be changed to suit the needs of the parameters. This resulted in three separate activities combined together to represent the crusher machine.

Hence, after the model was validated and verified to be in a working order, which represented the actual system, experiments could start to ensure further validity and the outcome of the model i.e. whether the model was able to carry out objectives.

8.3 Experimental Design

Before conducting simulation experiments, the user must decide a number of factors including but not limited to:

- The input parameters.
- Model run length (how long to run the simulation).
- Number of statistical replications.

Experimentation during model development phase should assist the user in making intelligent decisions regarding the above questions. The user should explore inherent model variability and the range of short-term behaviour. This should provide at least initial insight into appropriate model run length and number of replications needed for later experiments.

Model run length may be dictated by the nature of the system or the available data [84], such as when simulating 7 day's operations of the crusher machine, this will include the carrying out of all maintenance task on the machine, and/or other data-driven model where the data represents a fixed period. This particular project is however based on a maintenance period of 43200 minutes representing 30 days.

However, innate and high system variability together with a desire for a high level of statistical accuracy combined may require upwards of 100 statistical replications for each point in the experimental design [84]. Other models with less inherent variability may only require a few replications. In other models, model run length may be under the analyst's control. There is no rule of thumb for run length or number of replications; however, it should aid the research. For example, this study highlights very clearly that the parameter Drill *Head* has the longest life span; hence it will not be feasible to run the model for duration below a residing parameter. Rather, the duration should be dependent on enabling all the facets of the model to be carried out more than a single time. Hence, 43200 minutes is a suitable time that has been confirmed with experts in the field. This time allows all the parameters to be consumed a minimum of four times over. This should in reality enable a more adequate response from the simulation software as all the existing parameters and crusher machine as a whole is given the chance to excel.

8.3.1 Input Parameters

The input parameters gathered from the field visit that consisted of observations, historical data and interviews as well as persistent dialogue with experts from the existing manufacturing plant. The data with regarding to the crusher machine breaking down has been compiled over a period of 3 years, from which statistical averages have been derived in order to use within the models developed.

Data can be seen in appendix A, B and C representing data from year 2008, 2009 and 2010 respectively. Table 8.1 displays the data of the crusher machine from 2008, Table 8.2 and 8.3 also show the same data but of different years. This has been used for comparisons purposes in order to come to a consensus with experts as to the best representation for the model in terms of variables.

These tables actually dictate the input parameters for the models discussed in chapter 6 and 7, as variables from within these tables have been used to develop an accurate representation with the help of experts.

Appendix A, B, C indicate the number of breakdown occurrences, segregated into months and the time that it takes for the maintenance team to return the machine to normal working order. The time is then accumulated to highlight the monthly time the machine has been unavailable or the duration the machine has broken down for within each month. The Majority of the months have five breakdowns however some months only have four breakdown occurrences. The number of days is very important as it was used to calculate the MTBF. The tables show the number of hours spent on a monthly basis undertaking breakdown repair as well as a collated yearly sum after which an average monthly sum is highlighted.

The maintenance statistics highlight the input for the influencing parameters, their scheduled maintenance i.e. life span, and the time it takes for the maintenance team to carry out the scheduled tasks.

The data shown in appendix A, B and C enabled the development of an accurate representation of the base model as well as the MTBF model with the aid of expert opinions of which the results and experimentations will be discussed further.

8.3.2 Performance Indicators

The key performance indicators used throughout the research is represented by an array of quantitative performances which aid the fulfilment of the objectives and is as follows:

- Number of breakdowns
- The duration consumed undertaking breakdown repairs
- Parameter usage rates
- Average probability of failure
- Actual probability of failure (Bayesian probability)

8.4 First Experiment

Once the base model was ready i.e. validated and verified by experts, the MTBF breakdowns could be applied to see how many breakdowns occurred, the number of tasks carried out and the collated time that was taken or lost due to these maintenance issues. The MTBF was derived from appendix A, B and C, instead of using the MTBF of a single year, after much consultation a consensus was reached to use the lowest and the highest, hence the use of a Uniform distribution was applied i.e. uniform 8220, 8805 represents the MTBF.

The results of model 1 (MTBF model) showed the following results in table 8.1.

Table 8. Mean time between failure results of simulation model

Description	**MTBF Model**
Drill Heads changed	4
Average Drill head task time	120.3 minutes
Lubrication tasks carried out	9
Average Lubrication task time	33.1 minutes
Dusting tasks carried out	14
Average Dusting task time	26.2 minutes
Total task time (total inspection down time)	1146 minutes
Number of breakdowns	5
Duration consumed due to breakdown	1755 minutes
Average duration	351 minutes
Total Time Loss	2901 minutes/ 48.4 hours

These results were consulted with experts and were deemed as an accurate representation of the existing system and the results seem to be very near actual figures and within the consulted time frames according to tasks.

8.5 Second Experiment

Once the model was seen fit for purpose and use, the decision was made to add the usage ratios of parameters to understand the correlation of parameters with reference to the MTBF breakdown occurrences. This would show the breakdown occurrence and individual parameters usage as a percentage to highlight correlation.

The results are shown in Table 8.2 as follows:

Table 8. MTBF breakdowns and parameter usage rates

MTBF breakdowns	Parameters					
	Drill Head (%)		**Lubrication (%)**		**Dusting (%)**	
	Used	Remaining	**Used**	Remaining	**Used**	Remaining
Breakdown 1	**45**	55	**5**	95	**57**	43
Breakdown 2	**32**	68	**8**	92	**62**	38
Breakdown 3	**19**	81	**12**	88	**67**	33
Breakdown 4	**4**	96	**13**	87	**68**	32
Breakdown 5	**88**	12	**16**	84	**73**	27

From the results in table 8.2 it was very clear that breakdowns according to the MTBF did not correlate at all to any of the parameter usage rate. This led to further discussions with experts on the field it was evident that the time of breakdown did not show any relation to the parameters usage rate but rather, replicated a breakdown due to unknown reasons. Not a single parameter happens to surpass or consume above the 90% threshold, this lead to further dialogue with experts as all the data was accurate and the fact being, “in what position does this leave the MTBF model”. Further discussions lead to a consensus of the MTBF model being an accurate representation of the actual system; however, the model did not consider breakdown time with reference to breakdown occurrences and parameter, which is of crucial importance to the entire research.

The results in appendix A, B, C and E shows the number of breakdowns and the time consumed carrying out the repair for the breakdown. However it did not signify the time of breakdowns, this data was unavailable and had to be extracted from a subjective means. This aspect of the research was actually carried out and highlighted in previous chapters. It involved the interviewing of many employees of the facility i.e. the maintenance management team, this research brought to light that, breakdowns obviously did not occur within a fixed time and that breakdown could have occurred at any time. For example, if we move forward on the basis that five breakdowns occur every month, sometimes two or more breakdowns can occur in a single week, after which the machine may be in working order for the next two weeks, and then a further three breakdowns can occur within the final week.

With all the above in mind, and dialogue with experts, a consensus was reached i.e. the MTBF model although an accurate representation, was deemed unsuitable for predicting future breakdown occurrences as it was solely based on objective data which, although true, held no significance as it did not give importance to times and parameter consumption rates.

Further it was not deemed a logical representation of breakdown occurrences as breakdowns were guaranteed to occur according to the MTBF.

8.6 Third Experiment

The third experiment is based on the usage rate of parameters, this meant, for a breakdown to occur, the average collective consumption of the existing parameters have to surpass the 90% threshold. Also, the tasks are normally carried out when parameters reach 100% consumption, from the research gathered and extensive consultation with experts, it is apparent that many a times, breakdowns occur because the parameters are not adhered to as needed and they over use parameters.

Table 8.3 shows the results of the average consumption model after the MTBF approach was abolished as it held no real significance to the existing parameters but rather time and time alone. The table shows when breakdowns occur due to the average consumption of the parameters that are above the 90% threshold as discussed in the research which is seen to be the initial tell-tale sign of deterioration due of the parameters.

Table 8. Average Consumption Model Results

Description	**Average Consumption Model**
Drill Heads changed	4
Average Drill head task time	120.3 minutes
Lubrication tasks carried out	9
Average Lubrication task time	31.8 minutes
Dusting tasks carried out	14
Average Dusting task time	26.7 minutes
Total task time (total inspection down time)	1141 minutes
Number of breakdowns	2
Duration consumed due to breakdown	700.7 minutes
Average duration	350.4 minutes
Total Time Loss	1841.7 minutes/ 30.7 hours

The number of tasks and tasks time remain very similar as no changes have been applied to the tasks that need to be carried out, the small change in these figures are most likely a result of the software using random number generation.

However, Table 8.3 shows that breakdowns have actually been reduced to 2 compared to 5 from historical data and the MTBF model. This has resulted in the duration spent on breakdown repairs being reduced and the main objective of reducing the breakdown rate being accomplished, this model to can also be used to predict future breakdown occurrences.

Table 8.4 shows the parameter consumption with reference to the actual breakdowns modelled by the average consumption model. The consumption/usage rates of breakdown shown in Table 8.4 indicate a very good usage in breakdown, however, breakdown 2 seems to have consumed the parameter lubrication totally at 100%, dusting at 98% and the drill head has only been consumed 71%. This raised many questions, firstly, that two parameters alone can increase the average dramatically as shown in breakdown 2 of Table 8.4 , and secondly, that the lubrication parameter has consumed 100% at which point a change is required and should be considered.

The results of Table 8.3, when consulted with experts and were deemed to be very good as the objectives were met however they lacked validity as the questions were raised with regards to table 8.4. The average consumption usage of the parameters may in hindsight seem to be a feasible option. However, the fact that two parameters can increase the chances of failure meant it was seen as an unsuitable approach. Further, breakdown 2 highlighted that tasks needed to be carried out i.e. lubrication has consumed 100%. This approach highlighted a further area of concern from the experts i.e. the average approach did not give any significance to individual parameters indicating the point that, some parameters are more important than others and should be given higher priority as they can result in disruptions faster than other.

For example, the parameter Drill Head is of most importance compared to the simple carrying out of tasks such as lubrication and dusting, hence the drill head parameter's usage rate should add greater value to the possibility of a failure. The average approach considers influencing factors but holds the same value and importance regardless of parameters real value in actual systems. Therefore, the average consumption approach which in hindsight seems to be very good actually lacks validity and accuracy as highlighted by experts.

Table 8. **Average consumption model breakdowns and parameter usage rates**

Ave breakdowns	Parameters					
	Drill Head (%)		**Lubrication (%)**		**Dusting (%)**	
	Used	Remaining	**Used**	Remaining	**Used**	Remaining
Breakdown 1	**84**	16	**95**	5	**91**	9
Breakdown 2	**71**	29	**100**	0	**98**	2

8.7 Fourth experiment

Experiment four is where the Bayesian Network Modelling is taken under consideration and implemented via the chain rule within the Witness simulation software to aid the model. The Bayesian approach has been discussed previously in greater detail in chapter 6 and the implementation of the formula to the software has been explained in chapter 7.

However, it is very important to highlight key aspects at this stage as it helps to understand the results better. It is important to take the previous experiments into consideration and more importantly the consultations with experts with regards to the results. Firstly, the fact that expert acknowledgment of the average consumption approach to be unsuitable, due to not considering the value of individual parameters can now be rectified by the Bayesian approach via the means of the Conditional Probability Tables (CPT).

Figure 8.1 shows the CPT developed for the crusher machine where it takes into consideration the influencing parameters and their value as individual parameters. The order of importance and value is indicated by the use of arrows in figure 8.1, where drill head is at the very top of the table, after which lubrication and dusting processes follows. This data has been input with the help of extensive expert knowledge and collaboration in order to proceed over the hurdle of the average consumption approach.

The Bayesian approach calculates conditional and marginal probability based on this table in order to derive the probability of failure based on the influencing parameter and their importance accordingly.

Figure 8 Conditional probability table for Bayesian Crusher Machine

Based on the probability of the Bayesian approach, breakdowns will only occur when the probability of failure surpasses the 90% threshold which is the same percentage as the average consumption approach.

Table 8.5 shows the results of the Bayesian Model, the number of tasks remains the same and the time consumed by the tasks is the same. The results of the tasks are fit for purpose but will be scrutinised further with a stochastic approach to increases confidence and ensure validity.

The number of breakdowns seems to have increased now to three however it remains lower than the MTBF model which is seen to be an accurate representation. This does not mean it is wrong but rather the objectives of reducing the number of failures have been successful if the results there in can be validated. Based on the Bayesian approach only three breakdowns occur i.e. within the duration of 43200 minutes there are three separate intervals where the probability of failure surpasses the 90% threshold. This in essence has resulted in the reduction of time being consumed carrying out repairs enabling increased productivity from a management point of view.

Table 8. Bayesian Model Results

Description	**Bayesian Model**
Drill Heads changed	4
Average Drill head task time	120.3 minutes
Lubrication tasks carried out	9
Average Lubrication task time	31.8 minutes
Dusting tasks carried out	14
Average Dusting task time	26.7 minutes
Total task time (total inspection down time)	1141 minutes
Number of breakdowns	3
Duration consumed due to breakdown	1053.5 minutes
Average duration	351.2 minutes
Total Time Loss	2194.5 minutes/ 36.6 hours

Table 8.6 looks at the breakdown occurrences individually with respects to the parameter usage for further understanding. Breakdown one shows significant usage on all parameters with an average consumption above the 90%. Breakdown two indicates a high usage for the parameter drill head at 99%, however lubrication

is quite low using only 64% and dusting has consumed a significant 95%. Breakdown 2’s usage of parameters combined together does not exceed on average the 90% threshold. This highlights the point that, firstly, parameters do not need to consume above a certain threshold individual or collectively in order for failure to occur and that the average consumption may not be as effective as previously thought. This is even more apparent when the breakdown three is considered, where drill head has used 97%, lubrication and used 95% and dusting has only used a mere 40%. A very big difference in terms of averages and consumption of an individual parameter, this actually highlights the essence of the Bayesian model as indicated previously where individual parameters are given individual value and importance. Breakdown three shows the two most significant parameters usage rate to be very high with the third parameter very low, however, due to the value of individual parameters implemented within the CPT and formula applied to the simulation model, this still to develop into a failure. The same can be said for breakdown two i.e. parameter drill head of most importance and parameter dusting of least importance consuming majority of the usage combined has resulted in a failure although lubrication is quite low.

Table 8. Bayesian Model breakdown and parameter usage rates

Bayesian	Parameters

breakdowns						
	Drill Head (%)		**Lubrication (%)**		**Dusting (%)**	
	Used	Remaining	**Used**	Remaining	**Used**	Remaining
Breakdown 1	**84**	16	**96**	4	**92**	8
Breakdown 2	**99**	1	**64**	36	**95**	5
Breakdown 3	**97**	3	**95**	5	**40**	60

The Bayesian model at this current stage seems to be a very accurate fit with a robust system to calculate the most likeliness of a failure, this model can be used to predict future failure hence organise or strategies to combat such issue, enabling the reduction of machine breakdowns altogether as highlighted in experiment four. The results of the forth experiment were extensively discussed and analysed with experts after which a consensus was reached i.e. the Bayesian model is the most suitable and most accurate as it considered many different aspects that were highlighted in the initial experiments.

Due to the application of the Bayesian network model, influencing factors could be considered, individual value of parameters could be adhered to and most importantly, the objective of creating a tool to reduce the number of breakdowns and predict the occurrence of future breakdowns was achieved. Table 8.7 shows the combined results of the experiments to highlight the variance in the key performance indicators. The tasks remain the same throughout with very little variance in time consumed however, the number of breakdowns is different in all three experiments and hence the duration consumed is different. The average time on the other hand remains very similar and within the uniform time applied.

Another aspect of the results not yet stated is the actual times at breakdowns occur and the time between breakdowns; these are shown in Table 8.8 in ascending order. Table 8.8 allows similarities of the occurrence on breakdowns to be analysed if any and highlight a general overview in difference of breakdowns according to the models experimented.

Table 8. Combined results of all three developed witness models

Description	**Bayesian Model**	**MTBF Model**	**Average Consumption Model**
Drill Heads changed	4	4	4
Average Drill head task time	120.3 min	120.3 min	120.3 min
Lubrication tasks carried out	9	9	9
Average Lubrication task time	31.8 min	33.1 min	31.8 min
Dusting tasks carried out	14	14	14
Average Dusting task	26.7 min	26.2 min	26.7 min

time			
Total task time	1141 min	1146 min	1141 min
Number of breakdowns	**3**	**5**	**2**
Duration consumed	**1053.5 min**	**1755 min**	**700.7 min**
Average duration	**351.2 min**	**351 min**	**350.4 min**
Total Time Loss	**2194.5 min**	**2901 min**	**1841.7 min**

From the results shown in Table 8.8, it is clear that the average model's and Bayesian model's first breakdown in terms of time is very similar, however, the following breakdowns differ totally as do the time between failures. The MTBF model on the other hand has a very constant approach as it is implemented directly without the disruption of influencing factors. The MTBF models 1st breakdown does however occur at the earliest point in time, this is simply because the software actually halves the time of the breakdown time inputted in order to have an initial starting point i.e. the model chooses not to start off with a breakdown or after a breakdown repair but rather in the middle.

Table 8. breakdown times of the three models and variance

Descriptio	**Averag**	**Varian**	**Bayesia**	**Varian**	**MTBF**	**Varian**

n	e Model	ce	n Model	ce	Model	ce
Breakdown 1	8448		8478		4559	
Breakdown 2	17378	**8930**	20183	**11705**	13762	**9203**
Breakdown 3			30223	**10040**	22961	**9199**
Breakdown 4					32058	**9097**
Breakdown 5					41268	**9210**

8.8 Stochastic Analysis

The value of stochastic simulation as a tool for predicting current or future reliability of machinery, it helps to understand machine failures by using confidence levels developed through replications and exploring the changes that occur. A stochastic approach has been applied to the model constructed and discussed in experiment four representing a crusher machine and existing parameters. The consumption of these parameters results in the development of a probability of failure for the machine using the Baye's theory in order to calculate the probability of failure.

World class organisations invest vast amounts of capital into research and development to achieve an edge over competitors. This competitive edge depending on industry can be on a number of different aspects [87]. For example a new product or new technology that helps the organisation reduce cost or even making certain business processes easier, new technology can mean the invention of a new product or feature etc. In the case of the cement manufacturing industry, it is important to concentrate on how to increase productivity by reducing the occurrences of machine breakdowns in order to cater for current and future predicted demand [88, 89]. Their research and development may include the consideration of machinery, the type of machinery, new machinery or new systems that enable a prolonged usage of machinery.

Often planned changes result in the implementation of new strategies or philosophies that enhance productivity via the means of quality maintenance management. Maintenance of machinery is integral to all industries in order to maintain lead times and produce consistent quality products that are free from faults [90].

Hence, the ability to be able to predict the future reliability of machinery is pursued and encouraged by all industrial organisations in order to reach world class status.

The following sections will highlight the development of the stochastic model and is really an attempt to fine tune the results extracted, because stochastic is based on numbers generated randomly. The results that are extracted i.e. failure probability, should be different for every replication made, every replication will use different number streams and hence there should be a variance in the probability of failure for each replication. This will help to understand the strength of the results and further enhance the validity.

8.8.1 Stochastic Objectives

The objective of the stochastic analysis is to highlight the stochastic nature of the model, how the software is able to implement and generate random variables to enable an improvement in results by providing a more realistic approach.

8.8.2 Assumptions and Limitations

The stochastic analysis uses a simulation model previously developed (Experiment 4, Bayesian Model) to work out the confidence levels of machine breakdowns predictions. The Bayesian model constructed will have a running duration of 30 days (model running time of 43200 minutes).

The experiment will be replicated 50 times to achieve a strong result. The model is based on a single machine with three parameters. The model is based on the Bayesian Network Modelling, aided by the Hugin Software and further has the Chain Rule implemented to derive the probability. Witness Scenario Manager has been used to run test replication and extract results.

As mentioned previously, the main concentration will be the '*failure probability'* of the machine, to understand how the model reaches or extracts this developed probability it is very important to highlight certain aspects of the process that adds value to the results as follows:

The parameters that represent component parts have life spans which are now eligible to change because of the stochastic approach After their time is up, they need changing and hence inspections are now also eligible to change. This is the same for all three parameters; Figure 8.2 shows a screen shot of the Bayesian model, all the key performance indicators show times and usage rates. This in turn has a direct affect on the amount of life or usage rate of the parameter i.e. the percentage 'Used' and 'Remaining'. This means that, all the parameters in terms of time and usage will change at different intervals within the systems that are interconnected in order to extrapolate a certain outcome i.e. failure probability.

Figure 8 Bayesian Model Simulation Variables

Figure 8 Chain rule variables and probability

Hence, instead of looking at parameters separately or their key performance indicators individually, the concentration will be the failure probability that takes into consideration all the changes that occur to develop the probability using the Chain Rule. Figure 8.3 shows the variables that will change according to each replication, which added together, is the probability of failure.

8.9 Simulation Model

Witness simulation was used to create the Bayesian model in figures 8.2 and 8.3, the purpose of the model is to run reliability tests based on the information gathered and inputted into the system. The model is developed by the assembling of various elements and available modules that perform an array of different actions and calculations. As entities are created and travel through the model via other elements and modules, they interact with other elements that enable actions to be carried out and calculations to be made. The aim of the model is to simulate failures based on the existing parameters and their usage, hence as changes occur, the usage and amount of time is recorded, and as time passes the usage allowance is noted.

8.9.1 Overview of Simulation Model

Entities are created at a random and represent the three parameters that exist, after which they join the queue that represents a storage point where they await to be consumed by the activities representing the crusher machine. i.e. Drill Head has a life span of 10080 minutes, Dusting has a life span of 2880 minutes and Lubrication has a life span of minutes 4320.

Drill Head is the only parameter that has to be changed due to wear and tear, and the other two parameters are tasks that need to be carried out on the machine. Once the entities are created they simply join the queue waiting to be consumed, after they are pulled from the queue, they are due for an inspection represented by the setup time demonstrated in Figure 8.2 i.e. inspection down time, this is represented by the variable repair time to indicate the time needed to carry out tasks.

After the inspection that is implemented within the activity setup as entities enter the activity, they simply spend the designated life spans implemented, after which they leave and the process restarts. Within this process, variables have been implemented to take into account the different time allowances based on usage rates to develop calculations of probabilities. This can be seen in Figure 8.2 and Figure 8.3 via the use of counters that display an array of key performance indicators.

The simulation software generates pseudo- random numbers according to an array of different probability distributions. This is used to generate the component repair times and breakdown times from the various available distributions.

As the model is running, the value of the parameters is taken under consideration based on the usage allowances of the parameters, these conditions which are represented by a variable when joined together produce the overall failure probability that can make the machine come to a halt or breakdown. Further, fixed replacements based on timing and frequency can also raise aspects of concern i.e. does the component part need replacing or do the tasks need carrying out, hence the use of key performance indicators to show usage rate. So, if the machine does breakdown, the user can see how much of the usage allowances have been consumed and can also see if the component parts are responsible for the failure of the machine.

This simulation model will be replicated 50 times. A single replication of the model will produce one possible outcome, however every replication after that should produce or generate a different outcome, based on the development of pseudo random numbers. Therefore, it is very important to carry out many replication and use the mean of the results as the basis for the evaluation. The Witness Scenario Manager can execute multiple replications and the software calculates an array of statistics based on the entire model and the number of replications.

After much testing, validation and calibration, the model was completed as needed to reproduce conditions based on historical data and expert knowledge of the actual plant, machinery, parameters and situations. Hence, the life span given to the parameters is consistent with the actual tasks that need to be carried out.

8.9.1 Simulation Results and Analysis

The following tables and graphs have been selected which aid the understanding of the results. The results are based on the running of the model for 30 days in order to increase the confidence of the results achieved from the experiments carried out and verified by experts.

Table 8.9 shows the result of the total inspection time, this shows the variance in the total repair times consumed after 30 days, the 50 replications show the changes in time in graph 1, This is a total time that is compiled by all the inspections gathered together that go through the stochastic process every single time an inspection is carried out and further are attached to the pseudo-random distributions. Every single replication produces a different result due to the stochastic nature of the model as can be seen in Figure 8.4. From the results of graph 1, Table 8.9 has been derived by the scenario manager, where it calculates the mean, standard deviation and the minimum and maximum confidence level of 95%.

Table 8. Total Inspection Time by stochastic analysis of 50 replications

Std. Dev	23.0 5
Mean	1144
Confidence Level 95% Minimum	1135
Confidence Level 95% Maximum	1152

Figure 8 Total Inspection Times by Replications

The results show how the values deviate and if they fall within the minimum and maximum confidence level of 95% and what the mean inspection times are after 30 days is. This enables the management to make certain decisions based on increased understanding and to plan. This can be used more as a tool for the management to move towards a predict and prevent approach. Table 8.9 shows the average total time consumed by inspections. This can be further be scrutinised to derive the individual time of parameters inspection time to understand how much time can be consumed and the average of individual parameters. From the results of table 8.9 it can be seen that the average time is above the minimum and below maximum confidence level. This shows increased strength in the results achieved via the use of the simulation model. The results in Figure 8.4 do however indicate that at times, the results actually deviate below the minimum and above the maximum confidence level. This does not mean to indicate that the result is wrong but rather shows and validates the stochastic process and indicates how results can change.

The same set of results have been derived and used to increase the confidence of the probability of failure and to highlight the changes in the time breakdowns occur as shown in figures 8.4, 8.5, 8.6, 8.7, 8.8.

Figure 8.5 shows the time variation of when breakdown 1 occurs according to the replications made and table 8.10 shows the results therein. From the graph it is evident that the stochastic nature of the model allows breakdowns to occur at different times and the table indicates the standard deviation is rather small at 2.57 with an average of 8480. This average being in the middle of the confidence level shows great strength. Further analysis of the graph indicates that for the majority of the replications on an individual basis, the breakdown actually occurs outside the level of confidence. Hence to make decisions based on a single replication of the model after seeing the results of 50 separate replications would be very naive.

Figure 8 Breakdown 1 - 50 replications according to stochastic analysis

Table 8. stochastic analysis breakdown 1 results

Std. Dev.	2.57
Mean	8480
Confidence Level 95% Minimum	8479
Confidence Level 95% Maximum	8481

The results of breakdown 2 within the Bayesian model is shown in Figure 8.6 and Table 8.11, it consist of similar results compared to breakdown 1 however, at a different time and a slightly greater standard deviation at 4.50 as can be seen in table 8-14. The average is in the central of the minimum and maximum confidence level indicating a strong result.

Figure 8 Breakdown 2 - 50 replications according to stochastic analysis

Table 8. stochastic analysis of Breakdown 2 Results

Std. Dev.	4.50
Mean	20186
Confidence Level 95% Minimum	20184
Confidence Level 95% Maximum	20188

The results of breakdown 3 within the Bayesian model is shown in Figure 8.7 and table 8- 15, it consist of similar results compared to breakdown 1 and 2 however, at a different time and a slightly greater standard deviation of 4.94 as can be seen in table 8-15. The average is in the central of the minimum and maximum confidence level indicating a strong result.

The standard deviation of all 3 breakdowns seem to have increased ever so slightly at every breakdown so far, i.e. as model run time increases, however the average remains stable and constant.

Figure 8 Breakdown 3 Results 50 replications according to stochastic analysis

Table 8. stochastic analysis of Breakdown 3 Results

Std. Dev.	4.94
Mean	20223
Confidence Level 95% Minimum	20221
Confidence Level 95% Maximum	20225

The probability results in Figure 8.8 and table 8.13 is derived from a combination of variables as highlighted before in figure 8-2 and 8-3 from the life span of parameters and their usage rates. Table 8.13 shows the probability of failure which is a variable developed by the chain rule and implemented via the use of mathematical formulae. The value is the probability of failure after running the model for 30 days (43200 minutes) continuously. This table does not show or indicate the failure occurrences but rather simply shows which variable i.e. what probability; the model resides at after the run time of 43200 minutes. This allows the understanding of how the variables will inevitably change from a stochastic point of view after which the confidence of the results is extracted. Figure 8.8 also shows the *Mean* and the *Standard Deviation* in order to understand the results better in terms of variance. From Table 8.13 it can be seen that the standard deviation is very small at a mere 0.11, the minimum and maximum confidence levels only have a difference of 0.8% which is smaller than the standard deviation. These results show that the average or mean probability of failure from this set of replications falls within the minimum and maximum confidence level of 95%, this proves strong validity in results achieved. Figure 8.8 shows the variance of the probability although very small.

Figure 8 **Failure Probability Variance – 50 replications**

Table 8. stochastic analysis of Failure Probability Results

Std. Dev.	0.11
Mean	58.62
Confidence Level 95% Minimum	58.58
Confidence Level 95% Maximum	58.66

8.10 Integrating Maintenance Tools

8.10.1 Introduction

The effective management of maintenance is integral to the success of all organisations to improve equipment's lifespan, product quality, maintenance cost and the underlying production cost [145]. Hence, a consistent and effective maintenance system is of utmost importance in all industries in order to achieve the desired profitability and have a competitive edge over competitors.

Maintenance as a whole consists of an array of different strategies and tools combined together according to industry and organisation. No single strategy or tool is sufficient alone to achieve maintenance goals.

With the era of technology at hand with advanced computing and information technologies, more equipment and machines are instrumented with sensors monitoring on critical parts of machines to warn of potential failures before they occur fail so they can be corrected before they stop production. Integrated computerised systems are the core of intelligent maintenance as well as e-maintenance, where computerised systems aid development of management. This allows for more informed decision with regards to undertaking or being prepared to undertake maintenance of any kind.

Intelligent maintenance systems (IMS) Predict and Forecast equipment performance so that "Zero-Breakdown" status can be made a reality and not just a possibility of the past [34]. Zero downtime focuses on machine performance strategies to minimize failures. Data comes from sensors on equipment and machines and this information is gathered by the organisation i.e. quality data, past history, failures, repairs etc. Only looking at current and historical data from these sources can allow prediction of future performance.

Industrial organisations today depend on sensor-driven management systems that provide alerts, alarms and indicators. Most factory downtime is caused by these unexpected situations. There is no alert provided that looks at normal wear and tear over time. If it were possible to monitor the normal wear, then it would be possible to forecast upcoming situations and perform maintenance tasks before breakdown occurs hence the need for intelligent preventive maintenance.

Intelligent maintenance is to monitor equipment performance, and to ensure that if wear and tear starts to occur, there is enough time to carry out preventive maintenance on that particular area before failure. A machine can self-assess its health and trigger its own service request as needed and developed in this model with the automated response system. If this model works, then the machine can manage its own service performance, sending out alerts regarding preventive and corrective maintenances before an actual failure occurs. This will indicate ways to keep the system running in a high-performance manner and will most definitely result in leaner manufacturing.

However, many industries simply focus on the bottom line alone due to economies of scale, global economies and increased competition from throughout the world .The cost of downtime has a big impact on profitability. For example, if equipment starts to wear, machines may be producing parts with unacceptable quality and this may not be noticed for some time. Eventually, machine wear will seriously affect not only productivity but also product quality.

8.10.2 Maintenance Integration Overview

Integration of maintenance strategies, tools etc, can be segregated into two different integration methods known in the industry as "*hard integration*" and "*soft integration*" [146]. The *Hard* aspects are with regards to integration, which is aided by technology and computers, while the Soft aspects are to do with humans, and the integration of the general working organisation. The *hard* aspects to a certain extent represent a physical tangible means whereas the *soft* aspects are more to do with the mental approach of the work force making it intangible.

Now that the maintenance tool has been created using witness simulation software tool, it can be classed as a *hard* integration as it is a tangible means of assessing maintenance. This tool has to be integrated within the maintenance strategy of the organisation in order to derive the best possible results.

The two types of integration are directly related to prevention i.e. they aid unobstructed prevention of loss and thereby increase efficiency. Integration has to aid the unobstructed flow of information in all directions of the organisation regardless of hierarchy and managerial status in order to facilitate the decision making and planning processes throughout all levels.

Hard integration aspects of maintenance generally involves a computerised maintenance management system (CMMS) that deals with repairs and supplies, scheduling maintenance, condition monitoring technologies, built-in test solutions, reliability data on electrical and mechanical component parts, and decision support.

Soft integration aspects of maintenance deal with the staff including managers, technicians and operators etc. In general, this may be any one that has an interest, which affects the underlying maintenance strategy. However, technological advances in the manufacturing industry have given rise to increased use of machinery decreasing the involvement of humans directly in the manufacturing process.

The integration of maintenance tools and strategies is absolutely integral to increasing the availability and reliability of manufacturing systems in order to meet production plans and keep costs down.

Integration is achieved by the combining of optimal maintenance strategies to monopolise the advantages and evading the disadvantages of individual maintenance strategies. Hence, an affective maintenance programme should have different maintenance plans according to different machinery [147].

A machine system of one failure mode can have one of two states normal operating mode or failure mode. Figure 8.9 shows an example diagram of a single system that can either be in operating working state or in a failed state. The purpose of a good maintenance management system should be to decrease the failure rate and increase repair rate.

Figure 8 System Operating State, [146]

In actual maintenance applications, variables and attributes are scrutinised and used to determine the future reliability of machinery or component parts i.e the estimated time for preventive and corrective maintenance. Figure 8.9 shows the process in maintenance decision making and figure 8.10 enhances the process with greater detail as it shows the data flow from input to output.

Figure 8 Steps of Maintenance Decisions, [146]

Figure 8 Data Flow From Input Phase to Output Phase, [146]

This same system can be applied to the current developed maintenance tool. The simulation model developed provides very good information according to need. The existing parameters are shown according to usage and the failure rate is clearly visible indicating the chance of failure. The automated response system allows all aspects of the machine to be notified to all members, as message alerts arrive for when tasks need to be carried out and when tasks have been completed. Witness simulation can be kept fully integrated as other techniques and other tools are easily implemented within it.

Figure 8.11 shows inputs i.e. failures and downtimes, after which the tool are shown such as witness simulation which aids the decision making process output i.e. availability and MTBF.

This system also has to work closely with management and manufacturing philosophies such as J.I.T and SCM that talk about not only the need for software integration to help increase efficiency but also the need for a combined effort from industrial assets and industrial labour. The labour within an industrial organisation is the key to maximising asset utilisation and in return, the assets are the key to efficient productivity.

In today's economy, hard integration is used abundantly throughout all industries and philosophies. There are many examples one can take into consideration i.e. J.I.T is a software based system used in industrial organisation by world leaders such as Toyota in manufacturing cars. However, before J.I.T can be applied the enablers of J.I.T have to be adhered to as highlighted in the literature review. The enablers of J.I.T include the assets and labour force, and their responsibility. This example clearly shows the need to integrate the two types of integration to enable effective use of tools and strategies with an organisation.

The Master Production Plan (MPP), Material Resource Planning (MRP) and MRP11 have the same system in place, where technology is used to integrate the coordination of production and the materials needed with the aid of the available labour and industrial assets.

Wang [148] uses a stochastic approach to the decision making process for a condition based maintenance tool and Al-Najjar [149,150] uses a fuzzy approach in deciding the most efficient approach in maintenance. This highlights the fact that, even intelligent systems need to be validated and verified to ensure proper working order in order to achieve the best results and desired outcome.

The simulation model developed has been validated using Bayesian Network Modelling and Hugin Software. The essence of these techniques has been embedded into this software providing a dynamic platform that takes into consideration all influencing factors.

8.10.3 Discussion

As highlighted, the purpose of the thesis is to develop an affective maintenance tool for machine breakdowns. Witness simulation can be fully integrated with many other techniques mentioned within the thesis, as the chain rule has been implemented and the existing parameters have been considered by witness simulation.

Witness simulation alone is a hard integration process however; the actual processing of integration and consistent use of the software involves much soft integration with regards to adequate use. The simulation model developed clearly shows that parts needs changing and breakdowns need recovering i.e. highlighting the fact of employee involvement with the help of autonomous software.

Therefore, actual integration involved a combined effort of both types of integration as they work hand in hand. Neither one alone is sufficient to reach required levels of maintenance efficiency as technology has to inform management and management has to use technology to carry out tasks.

Hence, effective integration will decide the outcome of the tool developed, as even the best tool implemented in an incorrect manner can give rise to incorrect information and therefore cause more problems than intended good.

To conclude, integration must be achieved with careful consideration of all parties involved and without adequate integration of the new tool, it will be very difficult. A result upon which the thesis is based only considers a single machine and disregards the influence of the labour force.

8.11 Conclusion

After carrying out many tests and extensive discussions with experts within the existing plant where the crusher machine resides and is used on a daily basis, it is very clear that this set of tests was needed in order to highlight many facets of the machine and the software combined together. It enables experts to think outside the boundary of the machine alone and collectively involved the entire management team that included operators, technical staff, supervisors, and floor managers through to production mangers. The tests carried out highlighted many important aspects of the machine and existing parameters that were not considered extensive as should have in reality. For example, the value of individual parameters and the effects a single parameter can have on the failure on the machine.

The first revelation from the initial testing proved difficult although very important i.e. the MTBF model had been classed too subjective in terms of breakdown occurrences, although this model proved to be an accurate representation of the existing system. Once the usage rates were applied to the parameters for comparison purposes in order see the correlation, the results proved to be out of the ordinary although somewhat expected. Hence, the MTBF approach in predicting future breakdowns had to be abolished to develop a more stringent approach, as breakdowns would occur continuously after a fixed duration. The model did not represent breakdowns accordingly, or according to the usage rates of the parameters.

This led to experimenting breakdowns according to usage of parameters based on average consumption, which was initially praised by the experts as a good approach theoretically, however this view changed after experimentation was carried out. The initial findings showed that breakdown occurrences had been reduced to 2 breakdowns which was a very good result. In hindsight however, further scrutiny of the model and results revealed problems. Firstly, one individual parameter had consumed 100%, which affected the results and to a certain extent nullified that particular breakdown. On the other hand the realisation that any two parameters can increase the average consumption enabling it to surpass the 90% threshold raised further questions with regards to the validity of the model. This encouraged the experts to dwell further into the problem and a second issue was raised i.e. the average consumption and the MTBF models do not consider the value of individual parameters and how individual parameters can affect the occurrence of machine breakdowns. The key problems areas were taken under consideration upon which the consensus was reached, that the model was too optimistic with the number of breakdowns occurrences and therefore lacked validity.

The Bayesian model on the other hand enabled consideration of all the areas of concern that were highlighted in experiments 1 and 2. This model took into account the usage rates of parameters, the

CPT table enabled value to be added to individual parameters which were transferred into the simulation model by the application of the chain rule represented by the variables and probabilities shown in figure 8.2. The Bayesian model after taking all aspects into consideration showed the number of breakdowns had decreased compared to the MTBF failure model and had increased compared to the average consumption experiment. This model was thoroughly discussed with experts as were the results there in, upon which the consensus was reached that the Bayesian model was an accurate representation and the number of breakdowns were justified by the statistics of the model taking into consideration the machine and existing parameters.

8.12 Summary

This chapter highlights the stages in terms of experiments carried out and a thorough analysis is carried out with extensive consultation with experts. The final and most accurate model is scrutinised by a stochastic analysis to increase confidence of the results and explained.

Chapter 9

Conclusion

9.1 Introduction

This chapter discusses the use of simulation, and the value of the historical data that is analysed in order to extract the Mean Time between Failure and the Bayesian network modelling. It highlights the use of individual techniques and their application, concludes with a comparison that brings together the techniques, and elimination problems aspects leaving only the best approach in determining the occurrences of breakdown and predicting future breakdowns. The technique of using Witness simulation which represents the crusher machine and existing parameters with a series of elements as well as a logical command system aided by the implementation of formulae enables the use of a high quality animation in the simulation which improves the display at the human interface. Witness simulation has been used in countless industries for an array of different purposes by not only market leaders but world leaders in manufacturing such as Ford, a car manufacturer implemented simulation in order to optimise their production lines, Cadbury's, a chocolate manufacturer used simulation for new equipment design to test and validate the investment on robotic arms to aid the packaging process. BAE, a world-renowned defence and aerospace manufacturer used simulation to improve and increase production. This raises the simple question of “why do such organisations make use of simulation?” the answer to a certain extent is quite simply, “it works”.

Secondly, the development of “what if” scenarios that enables the effects of changes to be analysed, with results to being extracted and scrutinised. The development of “what if” scenarios can follow this cycle continuously, applying continuous changes until all parties reach a consensus of the model being fit for the purpose i.e. an accurate representation of the actual system. This is one of the biggest advantages of using simulation packages, although dependent on project it may very expensive due to the detail, expertise and time required. However, many industries have proved simulations to be an inexpensive process in the long term and when compared to applying direct changes to real time systems. The main benefit of simulation is the fact that, numerous experimentations can be done within a limited duration of time which requires reduced analytical requirements that are easily demonstrated [17, 25, and 91]. However, like all techniques there are limitations as highlighted previously i.e. Simulation model building requires special expert training and simulation modelling and analysis can be costly with the results of simulation involved in many statistics. One of the main disadvantages with simulation is the existence of programming errors [17, 25]. A simple inputted piece of data that is incorrect can alter the results of the simulation drastically giving the wrong results. Similarly, programming often uses theories of the way processes work rather than laws and hence theories are not always 100% correct. Simulation does however enable laws to be implemented via the use of formulae, which the program must follow.

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1.1 CONCLUSION

Bayesian network modelling has been presented in this work. A full specification, the process involved in developing the conditional probability tables (CPT) for each node are shown in detail with reference to existing parameters, and case study has been provided. The Bayesian network modelling is there after applied to the simulation model taking into account parameters usage ratios that generate the overall probability of failure. The failure rate is implemented via the use of programming formula, which replicates the Chain Rule used The probability of failure is thereafter validated by the use of Hugin software, which is actually used by the Bayesian network modelling. The Bayesian modelling approach has aided a reduction in the number of breakdowns and enhanced the logic of breakdown occurrences based on all influencing factors.

The initial base model and the actual model are based on purely historical data and statistical averages as highlighted in chapter 6. This is where the MTBF failure has been extracted in order to replicate the existing machine and the breakdown occurrences. In hindsight this was a logical approach dependent on historical data and objective means, however this approach was soon seen to be invalid to a certain extent as the breakdowns occurred within a fixed amount of time as expected. This was correct in theory, however in reality; this was not a logical approach as subjective information from experts and from the research under taken showed that breakdowns could occur at any random time and the fact that breakdowns should reoccur after the same duration over and over again in terms of machine breakdowns cannot be validated.

Further, the MTBF approach does not take into consideration any influencing factors other than time. In the real world of industrial machines, especially in the Libyan industry, there are many reasons why machine may breakdown. Chapter 2 highlights organisational challenges that aid the breakdown of machinery. An example of this is that management wait for a breakdown to occur by allowing parameters to be consumed fully and above their expected life span until a disruption is caused. After this, they will send out for technicians to fix the problem. They approach the entire manufacturing process on a traditional fail, fix philosophy under the pretence that they are making or deriving the maximum usage from parameters, and do not understand the ramifications of such an approach.

The historical data allows the extraction of the MTBF, which results in 5 breakdowns. This has now been reduced to three and all parameters can now BE taken under consideration with a dynamic approach. The aid of experts within this field was critical to the entire study undertaken, as this allowed a balance of both objective and subjective data to be considered and further enhanced to develop the best possible outcome keeping reality at heart.

All the research gathered from the field visit that consist of the historical data of machine breakdowns, individual parameter requisites, observational data and the techniques used to extract the best results from the data at hand, have been categorised by objective means. These objectives means were used to develop the simulation base model and the MTBF failure was applied to represent a true replication. The replication in hindsight is correct based on solely objective means without any further considerations as it can be compared to the data from the research. However this was not enough as all the information used for the MTBF model was based on time. “Time” is of the essence throughout this study, but time also changes. Initial data gathered lacked variability as all the time used were fixed static times. This data was simply obtained from operators/technicians that jotted the time interval down for the duration of breakdowns and repairs. Some variability did exist as the data was taken from a 3 year period after which the MTBF equation was applied to extract a further fixed time. Chapter 2 highlights the difficulty in extracting the right data, relying solely on the objective data is not a reasonable approach. Further, the results of the MTBF model indicated that breakdowns would occur continuously after a fixed duration with little variation. This result indicated and was found by the in the field to consist of little logic in terms of actual machine breakdowns that can occur at any given time. Hence, the results of the MTBF model lacked validity although IT represented the data accurately. Further, the MTBF failure model did not consider the ramification of individual parameters and the direct effects they can have on the machine. The initial research undertaken did not account for the actual reasons behind breakdowns but rather collated it all together under breakdowns as a whole with no real specifications. The MTBF has been established solely based on historical data and statistical averages as highlighted in chapter 6. This methodology although correct, cannot adapt to ever changing influencing factors and their effects on equipment and component parts.

The Bayesian approach allows influencing factors to be considered as shown in the case study and the Bayesian simulation model developed. The inclusion of these influencing factors has given rise to a better understanding of the stochastic model and greater confidence in the stochastic model [127, 128].

In Jones et al [11, 67], a case study was carried out that demonstrated the use of Bayesian network modelling to provide a more accurate approach in establishing the parameter failure rate. The Bayesian approach had aided the delay-time analysis used within the case study to establish superior results taking into consideration influencing factors. In the same essence, Bayesian network modelling has been implemented within the Witness simulation model to provide an improved method of establishing when failures should actually occur. The case study highlights the fact that the delay time analysis is too objective and subjective based on numerous statistical averages, which is similar to the MTBF model developed. The model developed proved to reduce the number of breakdown occurrences and greater assurance can now be given to results of this study given the addition of several influencing factors i.e Drill head, dusting and Lubrication relating to machine breakdown occurrences.

The stochastic analysis revealed the importance of carrying out replication. Variations do exist and replication has therefore be carried out in order to gain a greater depth of understanding of the results.

This new technique of having a integrated Bayesian system within the simulation model can be applied to all industries on any chosen machine. It can be used by the maintenance management and general management as a decision making tool to move forward to a “predict and prevent” solution eradicating the need of the traditional “fail and fix” approach.

Hence, this thesis presents a unique and original, advanced machine breakdown modelling approach via the use of a Witness simulation for supporting and integrating other management systems in all philosophies such as SCM, J.I.T and MRPll.

Chapter 10

Future Work

Simulation modelling as highlighted throughout this study can become a very complex undertaking at any point. This study was on a simple crusher machine that had three main influencing factors. Other influencing factors did exist but were overlooked by the use of assumptions in order for ease of understanding simplifying the entire model.

Simulation models should not be built for ease but rather to model reality and fulfil their purpose regardless of complexity. With this in mind, the need for further understanding and use of software is integral in any progress from here on onwards. This will allow greater scope and the building of much more viable models that are not dependent on the skills and expertise of individuals. This is also the reason why, organisations give the responsibility of model building to real experts of simulation who have numerous years of experience and work alongside them to reach the same goal.

However, the technique of using a Bayesian approach integrated into the simulation model developed within the study has proved to be a very forward thinking approach where the dynamics of the ever-changing influencing factors are considered. The discussion highlights certain constraints of the Bayesian approach, in particular its lack of availability with integrated systems for the implementation of Fuzzy logic, Truncated Mixtures and Credal network systems, all of which can be applied to the Bayesian modelling system but lacks validity, as implementation is limited. However, the use of simulation enables all the techniques to be considered and applied accordingly with the right expertise. Hence, in order to enhance the results further for means of comparison and education, these systems should be applied to the simulation model. Witness simulation allows these techniques to be implemented via the use of formulae providing a dynamic platform for testing.

After this, the model should be further developed in greater depth. The minimum number of assumptions should be used and greater importance given to influencing factors. All factors should be considered regardless of individual value as the Bayesian network modelling technique is able to handle vast amounts of variables dependent on the scope of the model.

In order to get a more precise and accurate result rather than a logical representation, elements need to be enhanced further as consideration of all component parts should be made regardless of effect or size.

By carrying out a stochastic analysis on the Bayesian model in a simple approach generated by the software, the importance is apparent as the replication shows variability in results. However, to carry out the analysis of the simulation output data thoroughly, the observations need to have a set of independent and identically distributed (IID) random variables.

In order for this to be accurate, the stochastic approach must be covariance-stationary and demonstrate no autocorrelations. A stochastic process beginning at zero minutes in time is unlikely to be covariance-stationery and can present autocorrelations [17].

Therefore, it is very important to research further to estimate the appropriate warm-up period for the machine in order to ensure that the output process of the simulation is in a steady state when gathering results. This will remove any initialisation bias in the simulation and enable the collating of results when it has reached a more stable state.

There are many discussions of initial transient and steady-state distributions and a list of relevant papers and books can be found in Glynn 2005, [129]. Hence, if the warm-up period is too short, the output stochastic process has not reached a steady state, which can provide misleading data and on the other hand, if it is a very long warm-up period, it can be a waste of time and resources. Therefore, an appropriate warm-up period needs to be estimated accurately.

Further, an increased number of replication should be carried out to strengthen the current results. As shown by the stochastic analysis carried out, variation in the results do exist, hence it only makes further sense to carry out further replications. There is no rule of thumb for the number of replication needed to reach a certain outcome however, the more replications carried out, the greater the understanding should be.

As the data acquired from the field visit and consultation was limited, much objective data was available however, overshadowed by the subjective means in the final phase where the Bayesian model was integrated into the simulation model making it very difficult to extract a balance. Hence further effort is required to extract the best possible data from all means possible.

The model developed currently is based on a model run time of 30 days. This can be increased to 3 months or 6 months, perhaps even 12 months. This may prove to be beneficial as increased results will be available over a longer duration of time. This should in essence develop greater understanding and enhance results, as the statistics that are provided by the Witness software package are statistical averages.

This research focuses on modelling a single crusher machine. This work can be extended to model breakdowns for any type of machinery needed or numerous models of the same machinery can be built. For instance, more than one crusher machine can be included in the system for the development of a “what if” scenario.

The user interface of the simulation model is currently a set of elements shown in the computer screen. A more user friendly interface can be implemented and integrated into the platform with powerful animation, making it easier for existing and new users. This can be done by making use of the 3-D animation available, which integrates various functions of the simulation platform into a single and uniform interface.

The main aim of this research has always been to build a simulation model that can be used as a tool in order to understand machine breakdown occurrences. Witness simulation is a very strong simulation package with numerous qualities. However, Arena simulation can also deal with very similar if not identical, scenarios and is more easily accessible for a new user. For Example, many books are available that are based on the Arena simulation package, while Witness simulation seems to have none, except for the user manual. It is very hard for a new researcher to develop simulation models using Witness. This area of concern to a certain extent falls hand in hand with the reason as to why, witness Simulation, in order to derive the best possible outcome, should be left to the expert so the virtues of simulation can be demonstrated justly.

Other work may include optimisation of computational efficiency, intelligent decision making techniques as highlighted previously i.e. fuzzy logic, and the quantification of the benefits gained from these methods.

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B. List of Author's Publications

The following are publications written by the author in conjunction with others during his PhD candidacy.

B.1. Journal Papers:

[1] E.M.Abogrean, M.Latif, "Integrated Maintenance and cost optimisation of Libyan Cement Factory using Witness Simulation" journal of management research vol.4 no.2,pp139-149.2012

[2] E.M.Abogrean,M.Latif,"Stochastic Simulation of machine break down in the Libyan cement factory journal of public administration and governance vol.2 no.2 pp95-105,2012.

[3] E.M.Abogrean, M.Latif,"Effective Maintenance enabled by the use of witness simulation in Libyan cement factory "journal of **International Journal of Advances in Management and Economics (IJAME) (Accepted publish in October 2012)**

[4] E. M .Abogrean ,M.Latif, "Explore Analytical Tools used for machine breakdown."Journal of quality in maintenance engineering Emerald group.

(under review).

B.1. Conference Papers

[1] . E.M.Abogrean, M.Latif,"Simulation of a Libyan Cement Factory"proccedings of the World Congress on Engineering 2010 vol III, London U.K ISBN:978-988-18210-8-9 international conference.

[2] . E.M.Abogrean, M.Latif,"Bayesian Network Modelling of M /.breakdowns "Matador conference –Manchester –AUG 5-7.UK 2012.

[3] . E.M.Abogrean, M.Latif,"Application of the Bayesian Network to Machine breakdowns using witness Simulation" International conference world congress on Engineering 2012 vol II in London, UK.

[4] Abogrean, E., and Latif, M., "Using Simulation to Optimise Supply Chain Management in a Libyan Cement Factory", 1st Faculty of Science and Engineering Research and Development Day at MMU, ISBN 978-1-905476-54-1, Dec 2010.

B. Selected Author Publications papers

B.1. Journal Papers:

B.1. Conference Papers

B. Selected Author Publications papers