A RISK-BASED MAINTENANCE METHODOLOGY OF INDUSTRIAL SYSTEMS

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Abstract

Maintenance is an essential task that must be carried out in an efficient and effective manner in order to sustain and prolong the physical assets of a company. Maintenance may be defined as any action which has the objective of retaining or restoring an item to a state in which it can perform its required function. Maintenance is therefore a valuable part of most industries today, helping improve productivity and output whilst reducing the costs associated with downtime in addition to eliminating failure of equipment. The goal of maintenance, like all other functions of any manufacturing company, must be a cost effective activity. Consequently, it becomes essential for a company to develop a cost effective maintenance strategy that will achieve this goal.

Delay-time analysis is a maintenance modelling technique which can achieve such goals in a manufacturing environment. Delay-time analysis, through the input of certain parameters, is capable of establishing an optimum inspection interval from both a downtime standpoint as well as a cost standpoint. The delay-time analysis concept has been further developed in this thesis in order to establish an environmental model. Alongside the downtime model and cost model, the environmental model gives a measure of the consequence of failure in terms of cost to both a company and to the environment. This environmental model has been applied to a company producing a product which is potentially harmful to both humans and the environment.

The use of delay-time analysis to establish a downtime model and cost model relies predominantly on objective historical data which, given the correct types of data, makes model development a powerful and accurate tool. The environmental model, however, relies heavily on subjective data and expert judgement in order to establish the required parameters. In order to overcome the inevitable

inaccuracies present in subjective expert judgement, due mainly to individual perception, the environmental model has been further enhanced using fuzzy set modelling.

The use of delay-time analysis to develop a model involves establishing several important parameters, one such parameter being that of failure rate (λ). This parameter forms an integral part of a delay-time analysis study but is established in a simplistic manner (i.e. number of failures/time). This parameter is established using historical information calculated using statistical averages. Understanding and identifying the influencing factors responsible for failure will serve to improve the understanding and increase accuracy of failure rate. This thesis examines and develops this parameter with the use of Bayesian network modelling. Bayesian network modelling allows differing influences responsible for failure to be considered in an exact and precise manner.

The findings of this research is that a methodology has been successfully developed, using delay-time analysis modelling, in order to aid decision making in a manufacturing environment. Further improvement of the delay-time analysis model was brought about with the use of fuzzy set modelling and Bayesian network modelling. The integration of both the fuzzy set model and Bayesian network model into the delay-time model has been conducted. A direct comparison has being drawn between the original delay-time model and the enhanced delay-time model in order to highlight the improvements of the integrated model.

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Abbreviations

BNM	Bayesian Network Modelling
CBM	Condition Based Maintenance
CPD	Conditional Probability Distribution
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DTA	Delay-Time Analysis
ECM	Effective Centred Maintenance
ETA	Event Tree Analysis
FMEA	Failure Mode and Effect Analysis
FPSO	Floating Production Storage and Offloading
FSM	Fuzzy Set Modelling
FST	Fuzzy Set Theory
FTA	Fault Tree Analysis
HPP	Homogeneous Poisson process
IARC	International Agency for Research on Cancer
IRT	Ideal Running Time
MMIS	Maintenance Management Information System
MTBF	Mean Time Between Failure
MUF	Main Unit Filter
NHPP	Non-homogeneous Poisson process
PM	Preventive Maintenance
PRA	Probability Risk Analysis
RCM	Reliability Centred Maintenance
TD	Downtime Incurred
TPM	Total Productive Maintenance

Chapter 1

Introduction

Summary

This chapter will discuss the background of this research and in doing so highlight the inherent problems which exist in industry today when applying delay-time analysis. The objectives and hypotheses of this thesis will serve to set out a logical structure of this thesis which is aimed at addressing the inherent problems outlined. The main research methodology is briefly discussed as well as the scope of the research.

1.1 Background of the research

Manufacturing, production and process industries today exist in a competitive market. There is an ever increasing need for improving efficiency, reducing costs and increasing safety, each intrinsically linked with one another. Maintenance is an integral part of any manufacturing industry, with a successful maintenance strategy delivering improvements to a company through increased productivity and efficiency whilst reducing the associated costs. The main aim of maintenance is threefold. Firstly, the equipment or system must have the highest possible reliability, secondly minimising the downtime of equipment and thirdly, minimising maintenance costs (Savic et al. (1995)). The total cost of maintenance is extremely difficult to calculate because of the number of factors which are affected when a machine or a piece of equipment fails (Ashayeri et al. (1996)). Factors could include: disruption to productivity, loss of productivity, downtime of failed equipment, quality of a product, inefficient use of personnel, repair time and repair cost. It is therefore essential to have an effective maintenance strategy

in place in order to remain competitive. Effective maintenance modelling can deliver greater efficiency in the form of reductions in downtime of equipment, optimisation of inspection intervals, and reduced downtime for inspections, with each improvement bringing about its own reductions in costs to the business. In the case of a company producing a product which is considered harmful to the environment, should failure take place, the prevention of failures become vital to the company. The inspection interval is often devised through subjective means, i.e. discussions with maintenance personnel. Maintenance is often performed for years without consideration to costs relating to inspection, breakdowns or downtime of equipment (Andrews and Moss (2002)). Advanced tools and techniques, which may be used for streamlining, updating and assessing current methods, are either unknown or inefficiently applied to a maintenance department. This may be down to a lack of knowledge, insufficient time allowed to study problems or situations, failure to understand modern techniques available or that there is a limited knowledge base which exists in the company.

There are several maintenance concepts and tools that enable equipment, machines or processes to be maintained in a cost effective manner whilst minimising downtime and maximising reliability. Such concepts and tools include Reliability Centred Maintenance (RCM) (Mokashi et al. (2002)), (Anderson and Neri (1990)), (Moubray (1997)), Preventative Maintenance (PM), Condition-Based Maintenance (CBM) or Predictive Maintenance, Total Productive Maintenance (TPM) (Brar (2006)) and Effective-Centred Maintenance (ECM) (Saferelnet (2005)). However, they must be utilised in an effective manner sometimes adopting several of these methods in combination to achieve cost effective results (Pillay and Wang (2003)). Applying modelling techniques such as delay-time analysis (DTA) (Christer et al. (1998)), Markov Modelling (Black et al. (2003)), (Saaty (1980)) and Bayesian network modelling (Wang and Trbojevic (2007)), (Khan et al. (2006)) to complex systems can be valuable. Delay-time analysis can, given certain parameters, establish an inspection interval based on minimising downtime or reducing inspection costs (Apeland and Scarf (2003)).

There are several examples for applying delay-time analysis such as gearboxes in buses (Leung and Kit-leung (1996)), winches on fishing vessels (Pillay and Wang (2003)) or an extrusion pump in a company producing copper tubing (Christer et al. (1995)). At present though, no research has been carried out applying such modelling techniques to an environmentally hazardous industry, taking into account environmental impact should failure occur.

1.2 Research objectives and hypotheses

The primary aim of this research is to develop a risk-based maintenance methodology capable of delivering a maintenance strategy. The development of an advanced risk-based framework is a vital part of this thesis as it sets the foundations of the whole project. The maintenance methodology will serve to establish inspection intervals based on reducing downtime, reducing costs or understanding the risks relating to an environmental impact. In order to achieve this aim, this thesis outlines three main objectives.

The first objective is to develop an advanced risk-based maintenance methodology for a manufacturing company. The maintenance methodology will provide a framework to optimise the maintenance and inspection activities of a company using qualitative and quantitative risk-based techniques. The modelling technique used for this exercise will be delay-time analysis. The optimisation will serve to either qualify the existing inspection policy that is being adopted or prove the inadequacy of the inspection policy. The result of the optimisation will be to establish an optimum inspection interval based on minimising downtime, minimising costs or minimising the environmental impact should failure occur.

The second objective is to develop additional models to support the implementation of the risk-based maintenance methodology. The modelling techniques used to achieve the objective of providing support and improvement to

the delay-time model is fuzzy set modelling and Bayesian network modelling. The integration of fuzzy set modelling into the delay-time model will address the problems associated when large amounts of subjective expert judgement are required. The integration of Bayesian network modelling into the delay-time model will further improve the delay-time model by considering the influencing events responsible for failure.

The third objective is to carry out a case study in order to demonstrate the risk-based maintenance methodology and the supporting models. This objective is a vital part of this 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 delay-time model in order to establish a maintenance and inspection strategy. As part of this objective, the case study will apply the maintenance methodology to a company producing a hazardous product. This will serve to establish inspection intervals based on reducing downtime of key equipment and reducing costs associated with maintenance and inspection. Additionally, this case study will assess the potential risks relating to the failure of key equipment resulting in an environmental catastrophe.

The objectives are set out in order to achieve the hypotheses of the research. The hypothesis being the development of a maintenance and inspection strategy capable of tackling a variety of circumstances found in industry, with special consideration placed on a company producing hazardous material. This hypothesis must utilise historical data, available data and expert judgement using risk-based tools and techniques.

1.3 Statement of problem

The main obstacle in developing a maintenance methodology which can be utilised by a variation of manufacturing industries is developing a maintenance methodology which can accommodate the differing types of information, products and processes of each. Each manufacturing company will have information relating to times and costs of inspections, maintenance and repair activities. The challenge of this thesis is to extract the required information, from objective and subjective sources, in order to produce a maintenance methodology. The process of gathering data, the use of existing data or reliance on expert judgement has shown to be a troublesome process in terms of accuracy (Wang (2005)), (Pillay and Wang (2003)), (Black et al (2003)), (Christer et al. (1995)). 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 (Christer et al. (1998)). The use of subjective data gathered from expert judgement 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.

1.4 Research methodology and scope of thesis

The methodology of the research carried out outlines a framework for the development of a delay-time analysis model for a manufacturing company. The research integrates fuzzy set modelling and Bayesian network modelling into the delay-time analysis model in order to improve the overall model results.

The research will discuss methods of understanding a manufacturing process, identifying the problems encountered and establish data that is required. This data

is interpreted and parameters are then established for applying delay-time analysis. Further development of the delay-time model is achieved by integrating fuzzy set modelling into the delay-time model in order to improve the accuracy and level of detail of the subjective information required. The delay-time model is further expanded by integrating Bayesian network modelling into the delay-time model. This introduction serves to re-evaluate and improve a key parameter of the delay-time model.

The scope of this research was to develop a maintenance methodology, utilising varying information from both objective and subjective sources. The purpose of the maintenance methodology is to a) reduce the downtime of equipment due to breakdown and failures, b) reduce costs associated with maintenance and inspection activities and c) reduce the risks associated with possible environmental damage due to failure.

This thesis is compiled of seven chapters. Chapter 1 has outlined a brief introduction relating to the background of the research, an introduction of the research objectives and hypotheses, a statement highlighting the problems currently encountered and the methodology and scope of this thesis.

Chapter 2 will examine the current literature which has influenced this study giving a brief overview of current maintenance concepts as well as the manufacturing industry in general. Following this overview, a detailed review of the current status in maintenance planning is considered. This will serve to draw attention to the possible inadequacy and limitation of the current status, thus demonstrating the need and justification of this research thesis. This chapter will close with a brief introduction to each of the risk-based modelling techniques used in this thesis namely: delay-time analysis, fuzzy set modelling and Bayesian network modelling.

Chapter 3 gives a detailed and exhaustive review of what will be the cornerstone of this research thesis, delay-time analysis. This review will scrutinise various applications of this modelling technique, examining some of the advantages and disadvantages of its use. The primary methodology is introduced in this chapter. The methodology includes the delay-time models, downtime model D(T) and cost model C(T) and environmental model E(T). The methodology developed has been applied to a case study in order to demonstrate the process involved.

Chapter 4 looks specifically at the problems relating to the standardisation of information when applying delay-time analysis to a maintenance department, specifically the delay-time environmental model E(T). This chapter outlines the inherent problem of combining subjective judgement and objective data. The introduction of a fuzzy set modelling methodology is outlined in this chapter dealing with the elicitation of such information. This methodology has been applied to a case study in order to demonstrate the process involved. The original case study from chapter 3 is re-examined with the fuzzy set modelling data replacing the original data gathered relating to the environmental model. A direct comparison between the original delay-time environmental model and the fuzzy delay-time model is then carried out. This comparison highlights the advantages of using fuzzy set modelling to elicit information from differing sources whilst overcoming the uncertainties and inaccuracies which previously surrounded this problem.

Chapter 5 will examine one of the key parameters when developing a delay-time model, this parameter being failure rate λ. The failure rate parameter was originally established (section 3.4) by dividing the number of failures by the time under consideration. This method though is based on statistical averages and does not consider the various events which can influence failure. Establishing and modelling the various parameters responsible for the failure rate of a system is considered in this chapter. A modelling technique known as Bayesian network

modelling is introduced in order to establish this parameter. Bayesian network modelling allows the influencing factors responsible for failure to be considered. Bayesian modelling also allows influencing events to change and update depending on the data available at any given time. A methodology has been developed and applied to the case study from chapter 3. The methodology establishes the failure rate parameter for use in the delay-time model. Similarly to chapter 4, the Bayesian model failure rate is integrated into the delay-time analysis model. A comparison is then conducted between the Bayesian network value for failure rate and the original value as used in chapter 3. The introduction of the Bayesian network model into the delay-time analysis model demonstrates an increased understanding and improved level of detail which could not have been envisaged originally.

Chapter 6 will examine the delay-time analysis model developed in chapter 3 and attempt to integrate fuzzy set modelling from chapter 4 and Bayesian network modelling from Chapter 5. This chapter will discuss the possible limitations of delay-time analysis which have been encountered during this research project. Overcoming these limitations by integrating both the fuzzy set model and the Bayesian network model will be examined and discussed. A series of comparison studies are developed in this chapter for each of the delay-time models namely, downtime model D(T), cost model C(T) and environmental model E(T). Each comparison is drawn from the original delay-time model developed in chapter 3 and the integrated delay-time model developed using fuzzy set modelling and Bayesian network modelling.

Chapter 7 will draw conclusions from the overall study. The chapter will begin by discussing the main conclusions and whether these conclusions have been addressed in this research project. This chapter will also ascertain as to whether this investigation has been a contribution to research. The limitations of this research will also be given together with possible future research which can expand and explore this body of research.

Chapter 2

Literature Review

Summary

This chapter will give an overview of a number of fundamental maintenance concepts that are currently available in industry today. An overview of the manufacturing industry will also be considered together with a brief discussion of the current status of maintenance planning in industry today. This chapter will then outline the need and justification for further research in this field. A brief introduction to the modelling techniques used in this research thesis is also presented.

2.1 Introduction

Before any research can take place there must be a need for further development. In order to establish whether there is a need for further development a thorough literature review of the topic area must be conducted. This chapter presents a thorough review of several key topics pertinent to this research thesis. Firstly, an overview of several maintenance concepts are discussed beginning with some fundamental definitions relating to maintenance and reliability and moving then onto key maintenance philosophies. Secondly, a thorough review of the current manufacturing industry is presented. This section covers the need for maintenance in industry, highlighting the increase of competition in the manufacturing industry. This overview also pays attention to manufacturing in the UK and the need for continuous improvements in the field of maintenance in manufacturing. Thirdly, a brief look at the current status of maintenance planning in the manufacturing industry is also discussed. Here a number of widely used and

often adapted maintenance concepts are scrutinised in greater detail, with discussion on some of the advantages as well as the pitfalls in applying such methodologies. In discussing these three important topics in manufacturing and maintenance, a genuine need and justification for further research is identified. A brief introduction to three analysis techniques which have been utilised in many varying industries is also presented, the techniques being: Delay-time analysis, fuzzy set modelling and Bayesian network modelling.

2.2 Maintenance concepts – an overview

Maintenance can be defined as ensuring that a facility, equipment or other physical asset continues to perform its intended functions. The ultimate goal of maintenance is to provide reliability to equipment, machines or processes that meets the business needs of the company. Reliability may be defined as 'the ability of a machine or components or equipment to perform a required function under specified conditions for a given period of time without failing' (BS EN 292). When maintenance is correctly developed and managed, it serves to preserve a company's asset to meet the need for reliability at an optimal cost. Maintenance may be broken down into categories, proactive and reactive. The reactive maintenance strategy has to respond to an identified need, for example, a breakdown of a machine or equipment. This strategy though relies on the speed of the maintenance department to respond and react to be effective. The overall goal of reactive maintenance is to reduce response times and reduce equipment downtime. The proactive maintenance strategy is primarily concerned with stabilising machines or equipment, relying on the detailed assessment of equipment and predictive maintenance or condition-based maintenance (CBM) techniques. The importance of maintenance is an indispensable function in a manufacturing enterprise (Ahmed et al. (2005)). The total cost of maintenance is extremely difficult to calculate because of the number of factors affected by the

action of a machine breaking down (Ashayeri et al. (1996)). Factors could include:

- Disruption to productivity.
- Loss of productivity.
- Downtime of failed equipment.
- Downtime due to inspection.
- Quality of product.
- Inefficient use of personnel.
- Repair time.
- Costs associated with all of the above.

Given these factors, the importance of maintenance should not be underestimated as it is one of the areas that contribute heavily to productivity. Not only can effective maintenance extend the life of the equipment but it can also improve production operations as a whole. A successful maintenance policy helps in reducing equipment downtime, improving quality and increasing productivity (Anderson and Neri (1990)).

There are several types of maintenance, one of which is Preventive Maintenance (PM). PM is maintenance that is performed before equipment failure takes place (Pillay and Wang (2003)). This type of maintenance involves the repair and maintenance of equipment in order to avoid unexpected failure during use. This method is often used in industry with routine inspections at set intervals. There are two types of PM that have evolved; the first is based on statistical and reliability analysis of equipment failure. The second involves the use of sensor monitoring of equipment in order to predict when failure will occur, this method is also known as condition-based monitoring. This method, however, can be costly and ineffective when used as the only maintenance practiced (Mokashi et al. (2002)). Following on from PM is a maintenance strategy known as Predictive Maintenance or Condition-based maintenance (CBM). Equipment is inspected

periodically to monitor their condition to observe the degradation which has taken place, a decision is then made as to whether repair/maintenance is required. This is only effective if condition monitoring is close to real-time and acted upon quickly. Success with this type of maintenance could have the eventual postponement of programmed maintenance tasks, thus reducing downtime of equipment. It uses non-intrusive testing techniques such as sensors, visual inspections or performance data in order to assess the condition of the equipment. Continual feedback of the condition of the equipment would allow the planning and scheduling or repairs before failure occurs. The data collected in CBM can be used in one of several ways in order to identify a precursor of failure or simply the condition of the equipment.

- Trend analysis. This involves simply reviewing the data to see if there is a downward trend toward failure (Newell (1999)).
- Pattern recognition. This is the understanding of the relationship between certain events and failure (Porrondo et al. (1998)).
- Tests against limits and ranges. Here alarms could be set at upper or lower limits to inform when a certain aspect of equipment moves outside this limit (Sherwin and Al-Najjar (1999)).
- Statistical process analysis. If there is published failure data on a component or system, a comparison of the failure data that has been collected on site with the published data can be useful to verify or disprove that the published data can be used for the analysis of a component or system (Arthur (2005)), (Pillay and Wang (2003)).

It is important to note that CBM should not be the only type of maintenance used (Pillay and Wang (2003)). Reliability-Centred Maintenance (RCM) is also used to optimise PM strategies. The focus of RCM is on maintaining system function rather than restoring equipment to an ideal condition. Another maintenance concept is that of Total Productive Maintenance (TPM). The aim of TPM is to maximise equipment effectiveness through increasing the availability of

equipment through the investment in human resources, this investment being through the utilisation of the workforce to become autonomous (Ahuja and Khamba (2007)). TPM is based on the promotion of PM through motivation and management of autonomous small group activities (Mohamed (2000)). As demonstrated in this section, maintenance has many facets for the multitude of applications in a manufacturing organisation. It is essential to have effective maintenance models and strategies in place in order to remain competitive. The challenge of any company is to employ the correct combination of maintenance tools and techniques which are appropriate to their business.

2.3 Manufacturing industry – an overview

Over the past 40 years the manufacturing industry has witnessed fundamental changes in its business. During the mid-1960s manufacturing capacity was less than demand which meant a company could sell whatever was produced (Hill (2000)). The rebuilding of some industrial nations, together with the emergence of others, saw output begin to outstrip total demand. This eventually led to overcapacity in many industries which in-turn contributed to the competitive nature of markets. Today, there is an ever-increasing pressure on manufacturing companies to improve the quality and increase products available whilst reducing costs in order to remain competitive. It is this competition that drives companies to achieve improvements in design and productivity in order to bring about cost reductions. The UK is the sixth largest manufacturer globally measured by output. The manufacturing industry makes up half of all UK exports, adding £150 billion to the economy each year. Investment in the UK is second only to USA with £26 billion, this compares to £15 billion for France and £3 billion for Germany (BERR (2008)). Competition, which may be characterised by technological innovations and a continuously changing market, places increasing pressure on each manufacturing company. In order to survive and thrive in the market, continuous improvement in the production systems to satisfy customer needs is required

(Gomes et al. (2006)). In the competitive market which the manufacturing industry is in, effective maintenance plays a key role in achieving a competitive strategy in industry today. There are many manufacturing approaches used in industry today, ranging from small batch manufacturing to mass production. The type of manufacturing approach to adopt will depend on the quantities to be produced, the type of product to be produced and the period of time available. Batch manufacturing, for instance, consists of workstations where several products can be manufactured on one production line. This method is generally used to produce seasonal items where demand is not continuous, for example, a bakery or a shoe manufacturer. At the other end of the scale is high volume, continuous manufacturing. This method is used to manufacture, produce, or process materials without interruption, for example, the oil and gas industry, automobile industry. The pressure on manufacturing companies is prompting senior management to examine each and every function of their business which includes manufacturing, or the maintenance of, to achieve a competitive advantage (Pintelon et al. (2006)). The maintenance function is therefore being looked on as a means of cost saving and gaining a competitive advantage. The integrating of the maintenance function with the other manufacturing functions has proved to save time and money when dealing with reliability, availability and maintainability issues (Moubray (2003)). Industry today adopts effective and efficient maintenance strategies such as condition-based maintenance (CBM), reliability-centred maintenance (RCM) and total productive maintenance (TPM) over the traditional reactive maintenance approaches (Sharma et al. (2005)). Along with the various manufacturing methods and maintenance techniques used in industry, there are a multitude of methods which attempt to bring about improvements relating to increasing productivity or reducing costs through eliminating waste. These 'improvement' methods include Lean Manufacturing (LM) and Six Sigma. Lean manufacturing is a system based on the philosophy of waste elimination, the removal of all non-value added activity from the manufacturing process (Phillips (1999)). Six Sigma is a philosophy that employs a structured continuous improvement methodology to reduce process variability and

remove waste from processes using statistical tools and techniques (Banuelas and Antony (2002)). The challenge, which comes from competition and the need for producing profits, compel companies into implementing maintenance strategies and productivity improvement techniques in order to compete in a constantly changing and competitive market (Samuel et al. (2002)).

2.4 Current status of maintenance planning in the manufacturing industry

Maintenance engineering and maintenance management are becoming more and more vital to the success of a manufacturing company. This is due to the high capital costs of machines and equipment as well as their high maintenance costs. Maintenance though can often be applied in a haphazard way, with poor integration of various maintenance techniques. Often a company will implement one or more of the best known maintenance techniques such as RCM, TPM and CBM without proper understanding of the maintenance philosophy or proper understanding of their own business. In many companies PM tasks can be perceived as unnecessary because they seem to be having little impact on plant operations. Conversely, PM can also be over utilised, in the sense that PM activities are performed more frequently than is actually needed. While each of these will certainly contribute to the success of the maintenance department, the way in which they are introduced can often lead to future problems (Coetzee (1999)). As a result, maintenance planning in the manufacturing industry today faces many challenges. There have been several case studies which have witnessed such challenges resulting in both successful and unsuccessful implementations, TPM implementation at the Rover Group being one such example (Bohoris et al. (1995)). This example highlights some of the pitfalls of implementing new maintenance concepts, in this instance TPM, into an automotive company. The maintenance departments across the company were detailed in a five-year strategy plan by the board of directors to implement TPM. Two previous attempts had been abandoned due to: 1) introduction of TPM on too

many machines at once, 2) lack of involvement of production staff and 3) TPM on equipment that was not essential to the overall process. The implementation was successfully achieved through a number of fundamental changes in the company, namely, gradual implementation of TPM and the implementation process was driven forward by production with the maintenance department assisting the process. This example illustrates a lack of planning of the implementation and how errors in implementing a maintenance strategy can be costly.

With the improvement of data collection techniques available to most manufacturing companies, improvements in accuracy of failure data, diagnosis and prediction can be realised. This data collection, through a maintenance management information system (MMIS), collects, processes, and transmits maintenance information and makes it available to maintenance personnel, managers, and those who need to make decisions which may affect plant operation and performance. Many organisations however have implemented such systems with differing levels of success (Labib (1998)). Successful implementation of such a system is dependant on both the planning strategy of the company and the maintenance practice in place.

Maintenance departments in the manufacturing industry often utilise a general PM strategy with the integration of other maintenance philosophies. This maintenance approach is then fine-tuned to suit each individual company. This method though has the potential to create problems such as establishing a root cause when a problem arises due to the multiple layered maintenance strategy. Implementation of new machines or equipment may also create problems as the existing maintenance strategy has to cope with this change.

2.5 The need and justification for further research

The manufacturing industry has a prodigious array of maintenance tools and techniques available at its disposal, along with an equivalent amount of software for the collection and manipulation of data, in order to establish a successful maintenance and inspection strategy. The problem exists however, that there is no single solution to determining maintenance and inspection strategies for a company. The amount of differing approaches that can be and has been considered makes choosing the correct strategy for any business a daunting task. The use of traditional maintenance and inspection techniques can be highly subjective, often relying on the judgement of maintenance personnel to establish inspection intervals. This method often comes down to the fact that if there are breakdowns then inspection should be increased or, if there are no breakdowns 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 company (Mohamed (2000)).

The use of risk-based analysis in industry has been wide and varied, some of which are discussed in section 3.1. The existing techniques used to establish maintenance and inspection regimes do not consider costs relating to inspection or breakdowns, nor do they take into account the probability or consequence should failure take place. This can be of vital importance to an industry where the product is a hazardous or even deadly product, for example the oil industry, gas industry or the nuclear industry. One of the main advantages of using risk-based approaches for establishing maintenance and inspection regimes is the use of probabilistic data together with key historic data, for example failure rate. It is worth noting at this point that the term failure rate λ or Mean Time Between Failure MTBF (a reciprocal of failure rate) is used as a guide to establish the interval at which a maintenance task should be carried out. Other information which is utilised is data relating to breakdown times and costs as well as inspection times and costs. Maintenance and inspection regimes can then be based

on minimising costs or minimising downtimes, whichever is considered important to the business. A risk-based concept able to take into account all of the parameters mentioned is that of Delay-time analysis (DTA). Delay-time analysis models information gathered using both historical data as well as subjective data. Delay-time analysis is capable of establishing inspection intervals for a maintenance department through the modelling of this information. This modelling technique however, has not been used to deal with failure of a component or equipment resulting in an environmental catastrophe. This thesis has addressed this problem by applying the concept of delay-time analysis to an environmentally sensitive product in order to establish an inspection interval based on minimising the risk of an environmental disaster. Chapter 3 introduces a delay-time environmental model which considers parameters such as human loss of life, human injury and collateral damage both residential and industrial. Each parameter is considered in terms of probability of occurrence as well as consequence in terms of cost. Lastly, but vitally, the environmental delay-time model considers the risks relating to whether the environmental damage can be reversed. The challenge in using the environmental model is the significant reliance on subjective expert judgement and the combining of this information with historic objective data. The elicitation of this information has been overcome in chapter 4 through the use of another technique known as fuzzy-set modelling. Finally, the parameter failure rate forms an integral part of the delay-time concept from the very beginning. It was thought that this parameter could also be improved upon as it is vital to the delay-time modelling exercise. This parameter is usually based on statistical averages and can easily fail to reflect a situation. The use of Bayesian network modelling was used to establish this parameter.

2.6 An introduction to the modelling techniques

The modelling techniques used in this thesis are delay-time analysis, fuzzy set modelling and Bayesian network modelling. The delay-time analysis model forms

the main area for this research with fuzzy set modelling and Bayesian network modelling supporting the original concept. Each model has been applied to a case study in order to demonstrate the methodology developed for each model. An introduction to each modelling concept has been included in this chapter for convenience.

2.6.1 Delay-time analysis

When a failure takes place in a component, a machine or a piece of equipment there are several signals which could give an indication to an impending failure, for example:

- Excessive vibration.
- Unusual noise.
- Excessive heat.
- Surface staining.
- Smell.
- Reduced output.
- Increased quality variability.
- Particles in oil.

It is often observed that a component or piece of equipment will give an initial sign of failure before its actual failure. The initial sign of failure being P and the failure being F, this is known as the P-F interval (Moubray (1997)). This however can only be possible if a clear potential failure condition exists. The conditions of the failure must display the following signs:

- The P-F interval must be consistent.
- It must be practical to monitor less than the P-F interval.
- The interval is long enough for action to be taken before failure.

Given this set of circumstances a concept known as delay-time analysis can be used.

Delay-Time Analysis (DTA) is a concept whereby the time h between an initial telltale sign of failure u and the time to actual failure can be modelled in order to establish a maintenance strategy. Delay-time is the period of time when inspection or maintenance could be carried out in order to avoid total failure. Figure 2.1 illustrates the delay-time concept (Arthur (2005)).

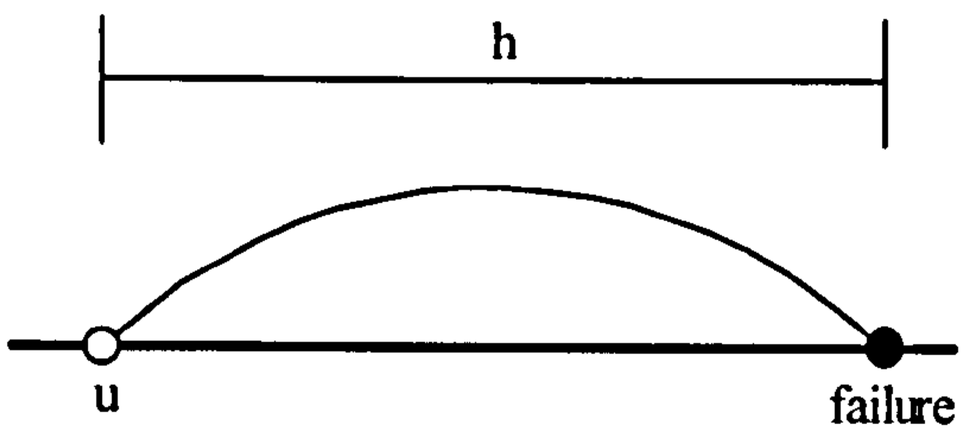


Figure 2.1. The delay-time concept.

To understand the advantages of the delay-time concept consider the example in figure 2.2. A time line with points on it signifies failures that have taken place. The item of equipment here is being maintained on a breakdown basis. The time of a failure is a random series of points.

Figure 2.2. A delay-time maintenance breakdown example.

Figure 2.3 illustrates the same failure point pattern but included is the initial sign of failure with each failure arising under a breakdown system.

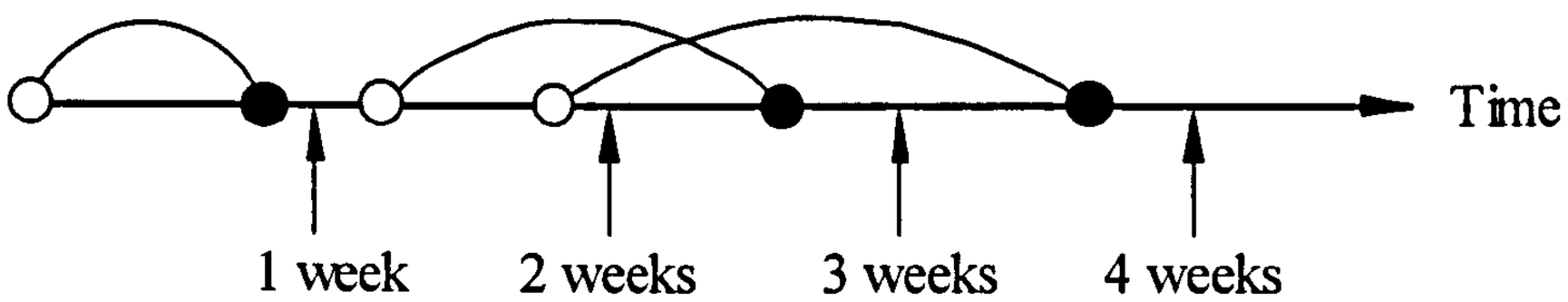


Figure 2.3. A delay-time example with initial signs of failure.

In this example increments of time have been included, in this case weeks, but the increments could be hours, months or even years. If the existing inspection period was that of a month or longer then this clearly shows that three failures would have taken place. Conversely, if the inspections would have been on a weekly basis, then two of the three failures would have been detected and prevented. Inspections though can be costly. Although two failures would have been avoided, three of the four inspections that took place at weeks 1, 3 and 4 during the four week period were unnecessary as week 2 inspection highlighted both failures. The cost of a breakdown can be high but the cost of inspections that are unnecessary can also be costly. Such costs, including, the time it takes to carry out an inspection, the production time that has been lost due to the inspection, the cost of man hours wasted both directly from the inspection task and indirectly from equipment operators not being able to perform their jobs, all contribute toward making inspections inefficient. Therefore it is vital to have the right balance between inspection and possible equipment failure. In this example if an inspection had taken place at two week intervals then two of the three failures would have been avoided whilst minimising unnecessary inspections.

The delay-time concept was first introduced by Christer (1973) where he used delay-time analysis to model the inspection policy for building maintenance. Following the argument of Christer and Waller (1984), the occurrence probability

of a fault arising within the period (*0*, *T*) with a delay-time of *h*, the probability of occurrence of this event is *f(h)Δh* where *f(h)* is the probability density function of the delay-time. If the fault arises in the period *(0, T-h)* the delay-time will expire before the next inspection at time *T*, which will result in failure. If a defect arrives in the interval ((*T-h*), *T*) then the next inspection will arise before the delay-time expires and the defect is rectified without causing a breakdown. Therefore the probability that a defect causing a breakdown is the chance it arises within (*0*, *T-h*), such a probability is ((T-h)/T), as can be seen in figure 2.4.

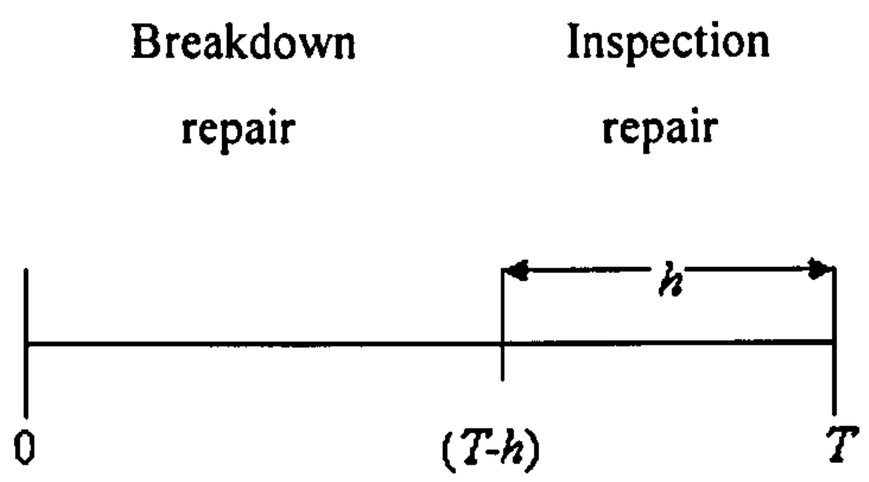


Figure 2.4 - Breakdown and inspection repair

The probability that a defect arises within the interval (*h*, *h* + d*h*) is *f*(*h*)d*h*. The combined probability of the events of a delay-time within (*h*, *h* + d*h*) and a defect arising within (*0*, *T-h*) is ((*T-h*)/*T*)*f*(*h*)d*h*. Therefore summing up all possibilities of *h*, the probability of a defect leading to a breakdown failure *b*(*T*) (assuming perfect inspection) can be expressed as follows:

$$b(T) = \int_0^T \left(\frac{T-h}{T}\right) f(h)dh \qquad (2.1)$$

This Equation (2.1) forms an integral part of the delay-time models which have been developed in this thesis. Equation (2.1) has been further developed and is included in each delay-time model, this is illustrated in section 3.3.10.

2.6.2 Fuzzy set modelling

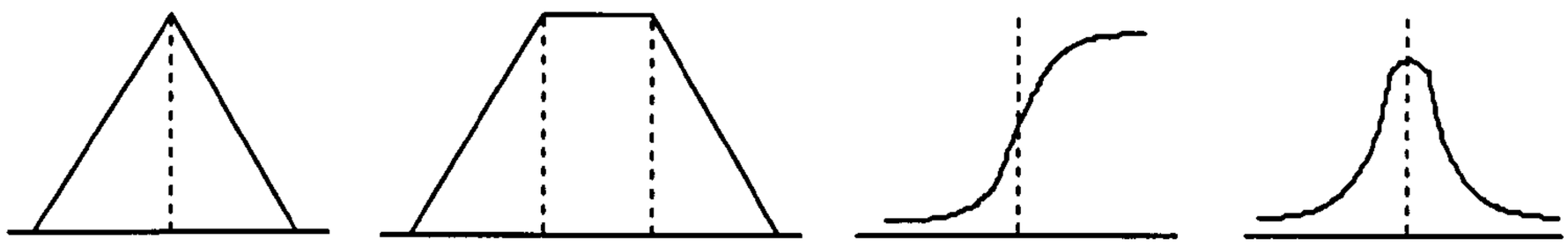
Fuzzy Set Theory (FST) was first developed by Zadeh in 1965. A fuzzy system is a system that uses imprecise or linguistic terms to describe a state. A system can have many 'states'. For example, the temperature of an engine may use the terms 'cold', 'warm', 'hot' and 'very hot', these temperatures may represent 0-250°C, 251-500°C, 501-750°C and 751-1,000°C respectively. Traditionally these states are referred to as 'crisp' variables but, although mathematically correct, are impractical in reality in many circumstances. With crisp variables the uncertainty of a state reaches its maximum at each border i.e. the temperature region 490°C - 510°C. An example of the impractical nature of crisp states could be that a temperature reading of 500°C may take place, it falls into the area of 'warm' but an underestimation of 2°C would alter the state to 'hot', leading to uncertainty in a maintenance decision to shut the engine down for an inspection or a repair. This uncertainty is ignored when dealing with crisp variables, known as bivalent set theory (Zadeh (1987)). In order to deal with these linguistic variables and the reality of a smooth transition from warm to hot, FST is used. FST abandons the sharp transition from one state to another thus allowing 'fuzziness' between states (Metaxiotis et al. (2003)).

Following on from this, if a universe X is made up of a multitude of x and various combinations of these elements make up set A on the universe, then for crisp sets an element x in the universe X is either a member of crisp set A or is not. From this example, non-membership is represented by 0 and full membership is represented by 1. This was expanded by Zadeh to accommodate various degrees of membership from 0 being non-membership to 1 being full membership, a membership between 0, 1 indicates the degree of membership $\mu(x)$. The difference between a crisp set and a fuzzy set is the membership function. Crisp sets have a unique membership function whereas fuzzy sets (denoted by $\tilde{A}$) have an infinite number of memberships to represent the situation (Ross (2004)). The typical notation used for a fuzzy set is illustrated in Equation (2.2).

$$\mu\tilde{A}(x) \in [0,1] \tag{2.2}$$

The symbol $\mu\tilde{A}(x)$ represents the degree of membership of element x in a fuzzy set $\tilde{A}$, therefore $\mu\tilde{A}(x)$ is equal to the degree to which $x \in \tilde{A}$ (where $\in$ denotes 'is a member of ' or 'contained in').

Different values can be assigned to a membership function depending on the purpose of the study or investigation. Fuzzy sets can also be represented by various shapes, again, this is dependant on the investigation or how best the data in hand is to be represented. The most common shapes used are triangular curves, S-curves, π-curves and trapezoidal curves (Pillay and Wang (2003)), these curves are illustrated in figure 2.5.



(a) Triangular (b) Trapezoidal (c) S-Curve (d) π-Curve

Figure 2.5. Various shapes that can be represented in fuzzy set theory.

The membership is generally shown in the vertical axis and ranges from 0 (non-membership) to 1 (full membership), the domain of a set is generally shown on the horizontal axis. A typical fuzzy set is shown in figure 2.6, highlighting the temperature ranges of an engine as previously discussed in the example above.

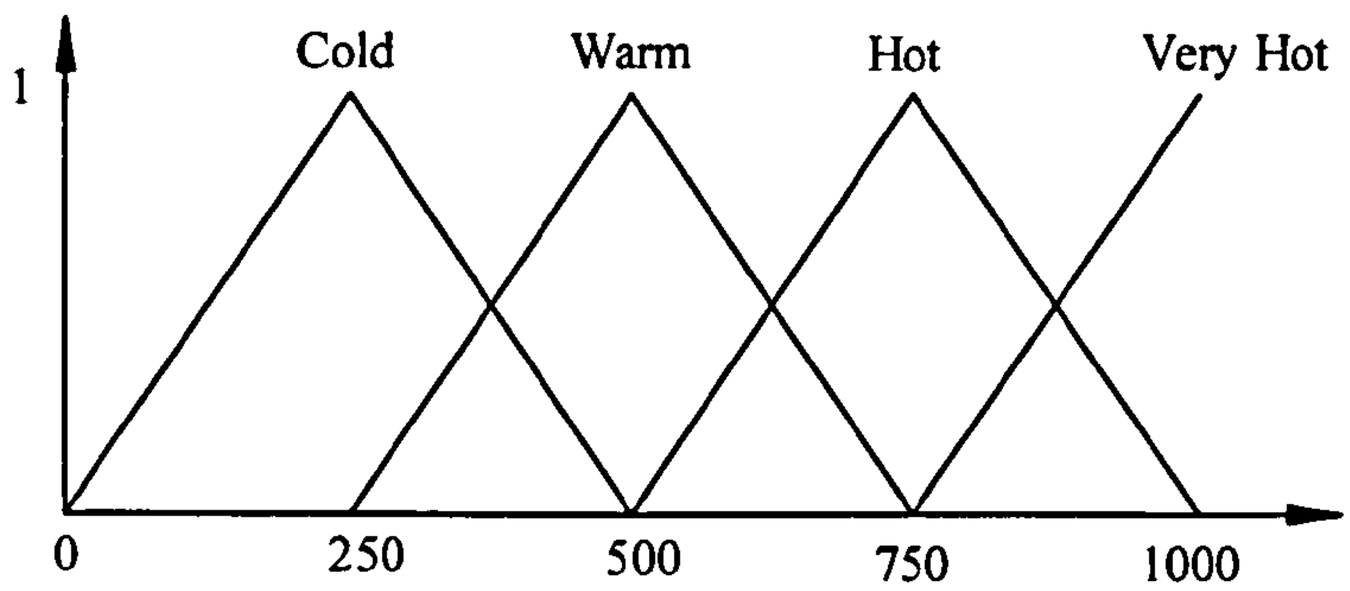


Figure 2.6. A typical fuzzy logic diagram illustrating engine temperature ranges.

There are two main types of membership functions which can be used namely, triangular and trapezoidal. The type of membership to use depends on the concept to be represented as well as the context in which it is to be used. Fuzzy sets, as illustrated in figure 2.6, can be represented by families of parameterised functions, in this case triangular functions.

2.6.3 Bayesian network modelling

Bayesian network modelling is an artificial intelligence tool used to model uncertainty in a domain or system (Nadkarni and Shenoy (2001)). Bayesian network modelling can help in identifying the relationships between variables given uncertainty in a system. The identification of critical variables whilst taking into account other influencing factors is also a valuable feature of Bayesian modelling. Uncertainty in any system can be due to factors such as:

- Inadequate understanding of the system.
- Incomplete knowledge of the system at a point in time.
- The system or parts of the system behaving in a random manner.

In its simplest form Bayesian network modelling relies on Bayes' theorem as its rule of inference, i.e. observations are used to update an uncertainty of a parameter or node in a Bayesian model. It relates to the conditional and marginal probabilities of two random events, calculating the posterior probabilities given observations of the two events. If two events A and B are considered where event A is the influenced node and event B is the influencing node, Bayes' theorem states:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{2.3}$$

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 on the basis of the arcs received. The nodes can represent any kind of variable or event. The variable or event could be a physical event, for example, a weather condition or equipment failing, a hypothesis whereby a theory or premise is put forward or an inferred variable i.e. not directly observed. A Bayesian network is therefore a DAG encoded with a CPD. In a Bayesian network structure an arc goes from one node (the source) to another node (the target) thus making a connection in one direction only (acyclic). A node is generally drawn as an oval or circle, representing the variable or event. The arc is generally a straight line with an arrowhead illustrating the direction of the link from the source node, often called the *parent* node, to the target node, often called the *child* node, representing the probabilistic dependence between the two

variables. If a node is an influencing node, i.e. no parents, then it has a marginal probability, if a node is an influenced node, i.e. a child, then this has a conditional probability. A simple Bayesian network modelling example is illustrated in figure 2.7.

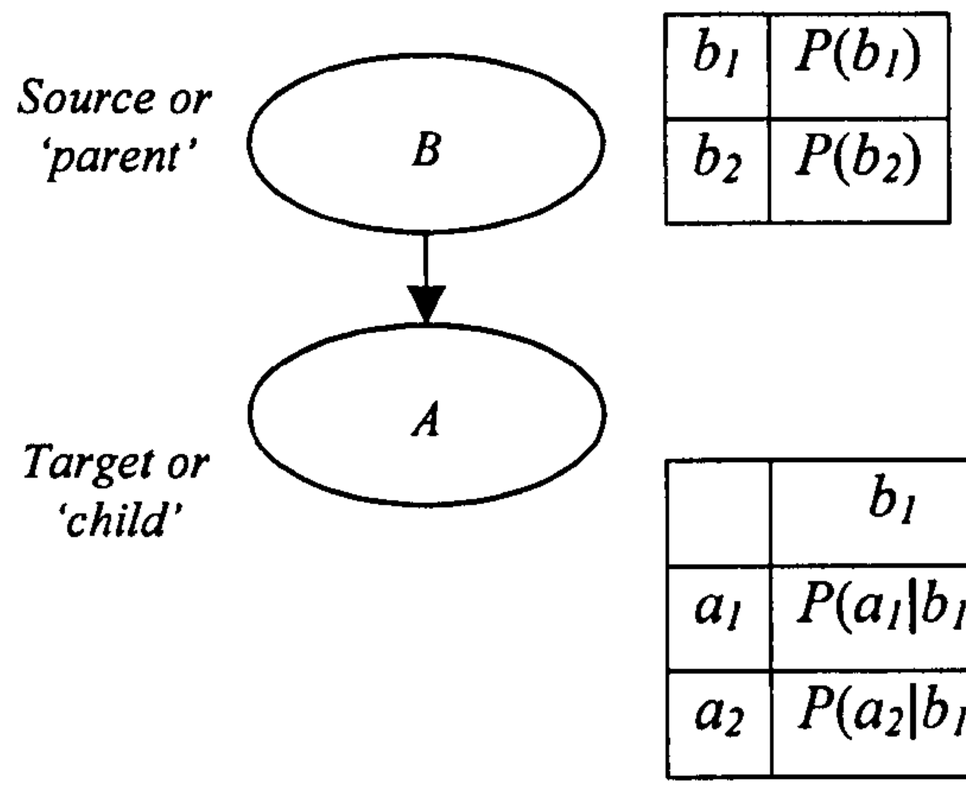


Figure 2.7. A simple Bayesian network model.

A simple Bayesian network consisting of event A and event B including their conditional probability tables (CPTs) is illustrated in figure 2.7. The CPT for event B has two states namely, b_1 and b_2 together with the probabilities $P(b_1)$, $P(b_2)$. The CPT of event A has two states a_1 and a_2 but the states are influenced by event B. The states in a node may signify the differing conditions of a node, for example 'hot' and 'normal' for event B and 'working' and 'failed' for event A. The probability for event A, $P(a_1|b_1)$, is described as 'the probability of state a_1 'given' state b_1' where the indication of conditionality is signified by the vertical symbol between each state '|' meaning '*given that*' or '*given*'. With B having an effect on A, A is conditionally described by posterior probabilities $P(a_1|b_1)$, $P(a_1|b_2)$, $P(a_2|b_1)$ and $P(a_2|b_2)$. The total size of a CPT child node is determined by the number of parent nodes in the network model, the number of states in each parent node and the number of states in the child node. The size of the Bayesian model requires careful consideration due to this fact. For example, three nodes

containing two states will generate a CPT for the child node containing 16 states, each requiring a prior probability to be established.

One of the advantages of Bayesian network modelling is its flexibility in allowing new nodes to be added to an existing model. It also allows existing information previously added to be updated as new information is gathered. An example of a simple Bayesian network is illustrated in figure 2.8.

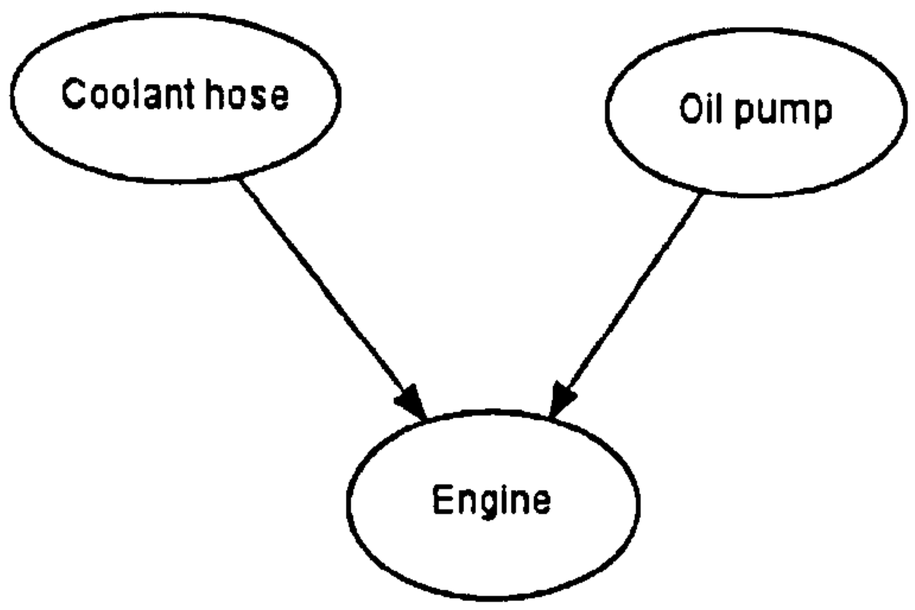


Figure 2.8. A simple Bayesian network model.

The example in figure 2.8 is that of an engine of a car. The engine will require oil to lubricate the engine and water to cool the engine, a lack of either will cause failure of the engine. The influencing nodes in this example are therefore 'Coolant hose' and 'Oil pump' with the influenced node being 'Engine'. The Bayesian network therefore consists of three nodes, 'coolant hose', 'oil pump' and 'engine' with each node consisting of two states. Coolant hose has two states, either 'leak' or 'no leak', oil pump also has two states, 'fail or 'working' and engine can have the state of 'fail' or 'running'. This example models the causal dependence between the coolant hose and the engine and between the oil pump and the engine.

The probability of a leak in the coolant hose will be an influencing factor as to the state or condition of the engine i.e. running or fail. A Bayesian network can not only visually represent the relationship between various nodes or events

(qualitative representation), it can quantitatively represent each node through a conditional probability table (CPT). A node with no predecessors (parent) is given a 'prior' probability distribution, whereas a node with predecessors (child) is given 'posterior' probability distributions. With each node given a CPT, a quantitative relationship between each node can be modelled. The CPT for each of the nodes 'Coolant hose', 'Oil pump' and 'Engine' is illustrated in figure 2.9.

Engine(Engine)

Oil	fail		working	
Coolant	leak	no leak	leak	no leak
Fail	100.0	100.0	30.0	5.0
Running	0.0	0.0	70.0	95.0

Coolant hose(Coolant)

leak	30.0
no leak	70.0

Oil pump(Oil)

fail	50.0
working	50.0

Figure 2.9. CPT for Engine, Coolant hose and Oil pump.

The CPT for coolant hose is given a probability value for a leak and no leak. In this instance there is a probability of 30% that the coolant hose will leak and a 70% probability that there is no leak. This data could be based on historical failure data, age of the component in question, or any other relevant variable. Similarly, the probability of the oil pump failing or working is 50%. The probability for the engine either running or failing is conditional on the condition of the oil pump and the condition of the coolant hose. Looking initially at the first column of the CPT for engine, there is a 100% probability of engine fail given failure of the oil pump regardless of whether there is a coolant leak. Looking now at the last column, given the oil pump working and with no leak present there is a 95% probability that the engine will run. In this example the child node (i.e. 'engine') has multiple parents (i.e. 'coolant hose' and 'oil pump'). In order to calculate the probability of the engine failing it is necessary to adopt the chain rule (equation (2.4)). The

nodes 'coolant hose' and 'oil pump' will be termed 'A' and 'B' and engine will be termed 'C'. The term C1 signifies the state engine 'fail'.

$$p(C1) = \sum_{i=1}^{2} \sum_{j=1}^{2} p(C1|A_i B_j) p(A_i) p(B_j) \tag{2.4}$$

P(engine 'fail') = P(oil 'fail') × (coolant 'leak') × P(prior engine 'fail') +
P(oil 'fail') × (coolant 'no leak') × P(prior engine 'fail') +
P(oil 'work') × (coolant 'leak') × P(prior engine 'fail') +
P(oil 'work') × (coolant 'no leak') × P(prior engine 'fail')

P(engine 'fail') = 0.5 × 0.3 × 1 + 0.5 × 0.7 × 1 + 0.5 × 0.3 × 0.3 +
0.5 × 0.7 × 0.05 = 0.5625 or 56.25% probability.

After populating the CPT for each node or event the modelling can also be carried out by using the software, *Hugin* (http://www.hugin.com), giving the same result.

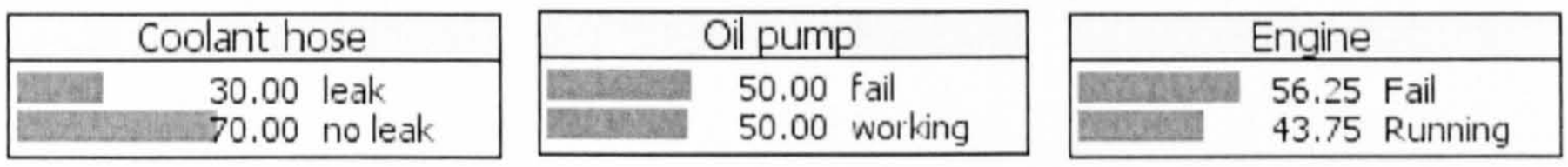


Figure 2.10. CPT for Coolant hose, oil pump and Engine.

From this example, illustrated in figure 2.10, it can be seen that given the conditional probabilities of both the coolant hose and the oil pump, the engine has a 56% probability of failing. The main advantage of Bayesian network modelling is that this information can now be updated giving a revised probability of engine failure. For instance, should a new oil pump be fitted, then the probabilities concerning the failure of the oil pump will be greatly reduced, which in turn will update the probability of engine failure. Amending the oil pump probabilities to

10% fail, 90% working gives an updated probability of engine failure of 21%, the updated CPT is illustrated in figure 2.11.

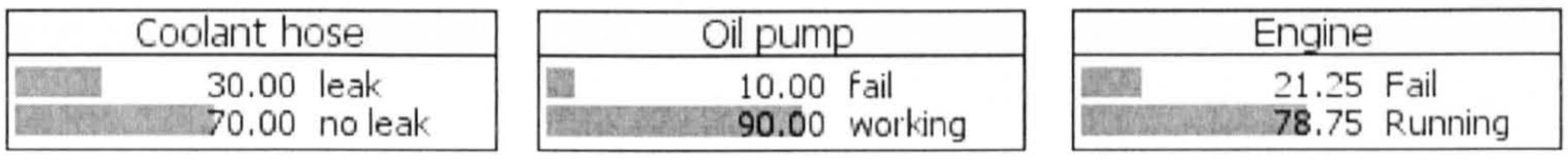


Figure 2.11. Updated CPT for oil pump.

To further demonstrate the flexibility of Bayesian network modelling, continuing with the above example, in addition to the replacement of the oil pump, a new coolant hose has been installed. The amended probabilities for the CPT of the coolant hose is that of 95% no leak. Given a further update of the model, the probability of engine failure is further reduced to 16% given this new information, the complete CPT for all three nodes is illustrated in figure 2.12.

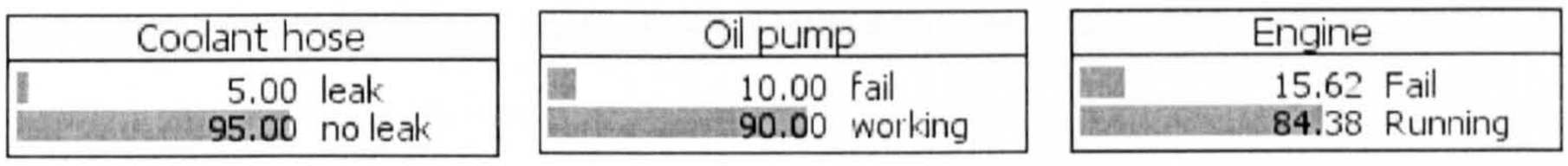


Figure 2.12. Updated CPT for Coolant hose.

2.7 Conclusion

This chapter has presented an overview of maintenance concepts as well as the manufacturing industry in general. The current status of maintenance planning has also been reviewed. From this a need and justification for research has been established in the field of risk-based techniques. A methodology using delay-time analysis (chapter 3), with supporting models using fuzzy set modelling (chapter 4) and Bayesian network modelling (chapter 5) has been developed as the main part of this research project.

Chapter 3

Methodology of using delay-time analysis for a manufacturing industry

Summary

This chapter has been written to give a methodology of applying delay-time analysis to a maintenance and inspection department. The aim is to reduce downtime of plant items and/or reduce maintenance and inspection costs, taking into account the possible environmental impact of a failure in terms of cost, both to the company and to the environment. The chapter also attempts to give a subjective measure of the consequences of such a failure in terms of cost to the environment, in monetary value to the company and the damaging effect to the company image. A methodology has been developed and applied to a case study in order to demonstrate the process involved.

3.1 Introduction

There are numerous risk-based techniques used in industry today for a wide variety of applications. There are several notable applications that serve to highlight the diversity of industries and techniques used. These include the optimisation of maintenance procedures using generic algorithms in the railway industry (Podofillini et al. (2006)), optimal maintenance decisions in the process industry improving the safety of plant and equipment (Kallen and van Noortwijk (2005)), probability risk analysis (PRA) and subsequent prioritisation of maintenance activities of the NASA space shuttle (Pate-Cornell and Fischbeck (1993a), (1993b)) and a sensitivity analysis of critical components using neural

networks (Marseguerra et al. (2003)).

Another technique, known as delay-time analysis (DTA), has also been applied to several maintenance areas in industry. Applications of delay-time analysis in industry have ranged from an extrusion press in a factory (Christer et al. (1995)) to the screening of cancers (Dekker and Scarf (1998)). Many papers (Christer et al. (1998b), Christer et al. (2000), Leung and Kit-leung (1996)) consider the application of delay-time analysis with certain assumptions attached, namely, perfect inspections and a constant inspection interval. Imposing these assumptions simplifies the mathematics in order to give a clear understanding of the methodology adopted. The downside of applying such assumptions is that the models, for most part, do not reflect reality. In Badia et al. (2002) a single unit system that alternates operating and idle time was studied. It examined a system with failures that are revealed at inspection and failures which are unrevealed at inspection. This took into account the probability of a failure remaining undiscovered at inspection, dealing with an assumption often made in the application of delay-time analysis; breakdowns can only occur when machinery or equipment is operating. A model which looked at imperfect inspections at non-constant intervals (Zhao et al. (2007)) using a non-homogeneous Poisson process (NHPP) in conjunction with delay-time analysis attempts to address this problem. In the next section, a selection of case studies will be examined in greater detail in order to obtain an understanding as to what has been previously achieved and what opportunities lie ahead in applying the delay-time concept to new challenges.

3.2 Applications of Delay-time Analysis

There are several interesting case studies to draw from using delay-time analysis utilising different information to good effect, some improving the maintenance policies and other studies verifying the validity of the existing

maintenance policies.

One study was to look at the maintenance problem of gearboxes that a bus company was experiencing (Leung and Kit-leung (1996)). The study investigated the possibility of improving the effectiveness of the existing maintenance policy. The tasks were to minimise maintenance costs, to estimate the reliability of the gearbox, to predict the consequences of possible maintenance policy changes and to predict the number of breakdowns each month for the year ahead. The need to identify an existing problem and its nature is vital to the success of any maintenance modelling process. Delay-time analysis was the central concept methodology used in this example. Following the argument of Christer and Waller (Christer and Waller (1984)) the models used in this example were the expected downtime per unit time function *D(T)* and the expected cost per unit time of maintaining the equipment *C*(*T*) on an inspection period *T*. An availability model was also developed in order to estimate the availability of a gearbox per month, based on ideal running time (IRT) and downtime incurred (TD) during a month ((IRT-TD)/IRT). Using the delay-time concept took the inspection period to 8 days compared to the current inspection interval of 30 days. A direct comparison was then calculated between the current inspection policy of once a month and the delay-time inspection policy of eight days using three criteria, cost, utilisation and downtime. The monthly maintenance cost would have risen by nearly four times the amount under the delay-time inspection policy, the required workload would have risen 36%. It was therefore suggested that they continue using the current inspection policy. However, this example was one where the company's inspection policy was correct for them even though the delay-time inspection policy would have reduced downtime, the cost of employing this strategy was too great.

A similar case study that was carried out was that of a winch on a fishing vessel (Pillay et al. (2001)). Again as in the previous example, a downtime estimation model and cost estimation model were used but differently a safety

criticality estimation model was also developed. The data gathered in this example came from a subjective source. Having established a delay-time for each of the three models, downtime estimation, cost estimation and safety criticality, the inspection period when downtime is minimised was that of 5.18 operating hours, 7.24 operating hours when the cost is minimised and 17.28 when safety criticality is minimised. Expected cost was plotted against expected downtime, this generated the best compromise between cost and downtime. A compromise between the three was also established when downtime, cost and safety were plotted together. This information could be extremely useful for high maintenance equipment or frequent breakdown equipment.

The two assumptions, perfect inspection and constant rate of defects over time, simplify the mathematical modelling of a system but can be misleading in some cases to portray the real-life system. Most case studies tend to use perfect inspections, this though is dependant on the equipment being studied. In Pillay et al. (2001) and Arthur (2005) the studies assumed perfect inspections. The introduction of non-perfect inspection (Christer et al. (1995)) brought a different concept to inspections. If equipment is complex it has been shown that there is no guarantee after an inspection that the equipment or system is now in a perfect condition. This was utilised in a case study of an extrusion press in a factory. This is useful as it gives a quantitative measure of how imperfect the inspection was, i.e. the probability r of detecting a fault. This case study also demonstrated the use of objective data which was termed 'the objective method'. It demonstrated that the model output values for downtime percentage compared to the objective data, which was gathered from production records and failure data, were in close agreement, confirming that appropriate delay-time analysis modelling can be used in supporting maintenance policies based on objective information.

A further case study (Christer et al. (1998a)) of a company manufacturing brake linings highlighted several key points in the effective use of maintenance and the positive results that delay-time analysis contributed to. A piece of

complex equipment was used in this study and data gathered was over a 13-month period. The problem highlighted with this case study was that of identifying and removing a fault at inspection or more accurately with the probability of it. The figure of 13% was established from discussions with their maintenance engineers. Their current 3-week inspection policy was unsuitable. An optimal inspection period was established as that of once a week which brought about a 30% reduction in downtime. Also the probability of detecting a fault during inspection was that of 13%. If measures were taken to improve the engineering ability to identify and rectify this figure then significant gains could be realised, reducing downtime from 7.2 hours a week with a 3 week inspection policy to 3.4 hours with the same inspection policy. Another point made during this study was to establish which components had the shortest delay-time so that these items would be targeted at inspection firstly, thus further reducing downtime. The data, as previously discussed, that existed was that of times of failures and times that maintenance was carried out but no data existed of the condition of the equipment at inspection or the actions taken at inspection. This, though not uncommon in the industry, highlights the importance of useful data underlining the lack of awareness from the management of the value of this type of detailed data.

A delay-time analysis, which was applied to a vibration analysis inspection for an offshore oil and gas water injection pumping system (Arthur (2005)), was carried out in order to establish a cost effective inspection policy. The critical systems are currently maintained using a condition based maintenance (CBM) policy with an inspection cycle time of once a month. Firstly, data was collected from the computerised maintenance management system and assessed. From this information any planned maintenance was disregarded and any unplanned (corrective) action was further scrutinised. The nature of the work carried out was established and dominant failure modes were highlighted. The failure modes were the bearings from the motor, the gearbox and pump of the injection system and the impeller and shaft from the pumps. This data was compared to an industrial reliability databank (OREDA (2002)). Converting both sets of data to a common

base of MTBF showed the observed data and reference data as comparable between each other giving credibility to the observed data. The mean delay-time was then established together with the optimal inspection interval. The costs of failure and inspection were then established and the results proved that a monthly inspection period was not cost effective and a move to a 5-month inspection period would bring a reduction from an annual cost of inspection from £25,200 to £4,200, a saving of £21,000.

3.3 Methodology

In order to develop a maintenance model using delay-time analysis a methodology needs to be developed in order to give the process a framework. Delay-time analysis can be used as a tool for reducing the downtime, *D(T)* (Christer et al. (1995)) of a machine or a piece of equipment based on an inspection period *T*, given the probability of a defect arising within this time frame *b(T)*. For a particular plant item, component or series of machines, delay-time analysis is useful because the equipment in question is generally high volume and high capital expense, therefore any reduction in downtime due to breakdown or over inspection can be beneficial. As with the modelling of downtime per unit time, it is also possible to establish a cost model, *C(T)* (Leung and Kit-leung (1996)), again based on an inspection period *T* and probability *b(T)*, this model estimates the expected cost per unit time of maintenance. This modelling has also been used for safety criticality (Pillay and Wang (2003)) on a fishing vessel giving safety criticality of a failure and operational safety criticality. Given these examples of how delay-time analysis can be applied, one area that could benefit greatly is the impact of a failure leading to an environmental accident. A quantitative approach of assessing the cost to a given company of an environmental accident could give a measure of the importance of and the monetary value gained in avoiding such an event. A flowchart of this methodology is illustrated in figure 3.1.

A methodology for applying delay-time analysis is proposed as follows:

- Understand the process.
- Identify the problems.
- Establish data required.
- Gather data.
- Objective data analysis.
- Subjective data analysis.
- Advantages and disadvantages.
- Validation of the delay-times and the distribution.
- Establish assumptions.
- Establish a downtime model D(T), cost model C(T) and environmental model E(T).

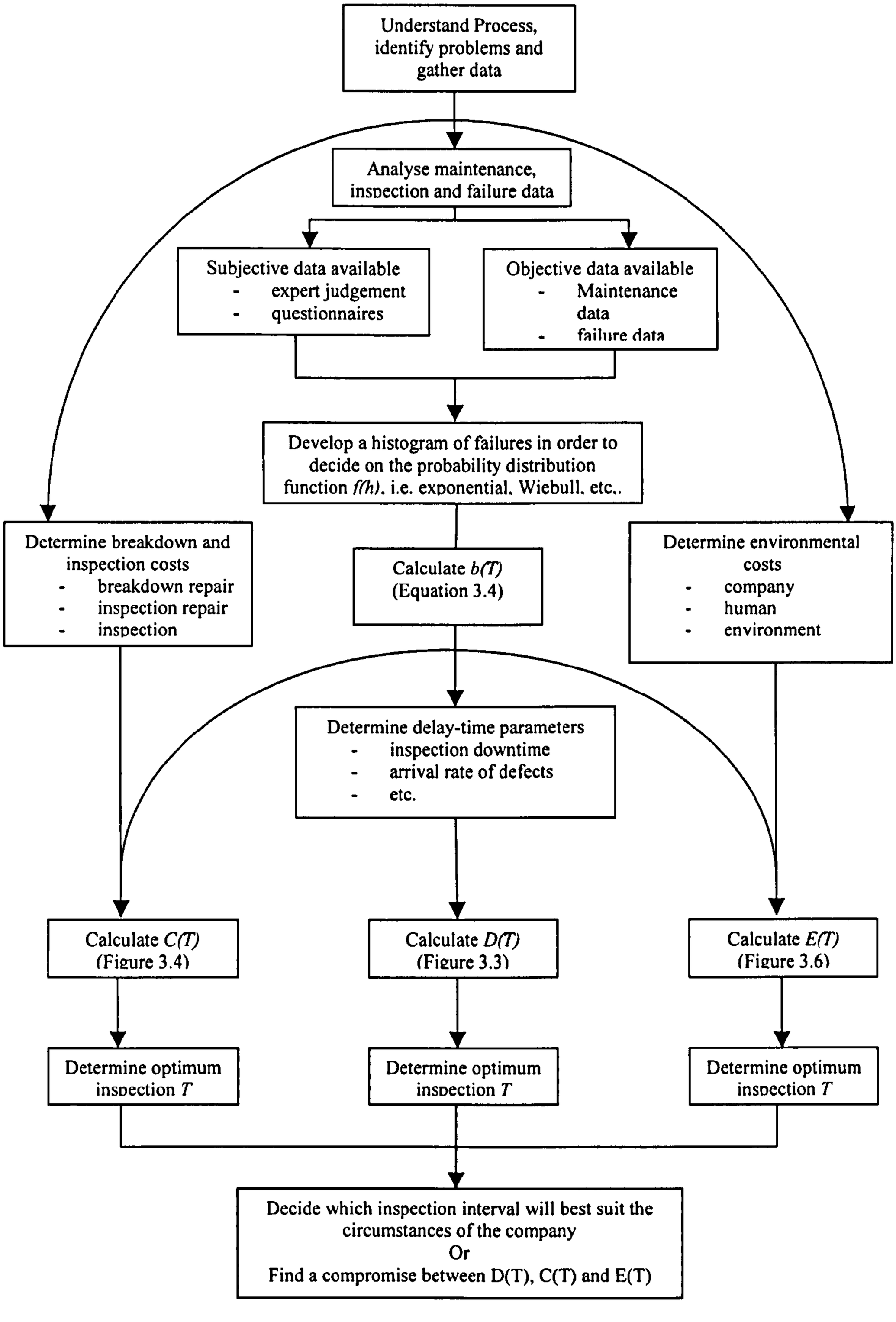


Figure 3.1. A flowchart of the delay-time analysis methodology.

3.3.1 Understand the process

Before the development of any maintenance model is carried out a thorough understanding of the processes involved is essential. Insufficient or inadequate work in this area will almost certainly spell disaster in the task of understanding the problems of a company. When understanding a process it is equally important to consider the tasks carried out at inspection as well as during maintenance. It may be the case that there are several parts that are inspected regularly but seldom fail or a component that fails regularly might be overlooked because it is inexpensive to correct.

3.3.2 Identify the problems

Several techniques using risk-based analysis can be useful in this phase of the study including event tree analysis (ETA) or failure mode and effects analysis (FMEA). ETA can be used to identify various possible outcomes given an initiating event. An example of this is a component failing giving an indication to an area of equipment or process that requires further investigation. FMEA can identify possible failure modes and the effects on the system but can also give a potential severity to the effect, this being most useful when looking at environmental or safety critical items. Having spoken to maintenance managers, production managers and key shop floor staff, a thorough understanding of the process should now be possible. Most problem areas should now be highlighted and problems evident. Problems such as frequent breakdowns, common cause of breakdowns and lengthy breakdowns, especially in the case of high volume equipment should all become apparent. Care should be taken as to whether a breakdown is a maintenance issue and not an engineering issue or operator issue. An example of an engineering issue may be working to an incorrect drawing or procedure, an operator issue may be the performing of a task using incorrect tooling or running a machine at a higher rate than it was originally designed to

run. Once the key plant items have been identified together with a list of dominant failures associated with the item, data can then be gathered.

3.3.3 Establish data required

Data can come in many forms from maintenance departments and more often than not be extremely detailed, however for the purposes of producing a delay-time model this information is often unusable (Christer et al. (2000)). The majority of data gathered by maintenance departments is generally the name of the equipment or the part number to have failed, the repairs made including spare parts used and the time the repair or inspection has taken to return the equipment to production. Therefore the type of data collected is important along with some basic assumptions for the equipment or component investigated. The types of data required for a delay-time analysis (Pillay et al. (2001)) are as follows:

- Average downtime due to inspection, d.
- Average downtime for a breakdown repair, d_b.
- Arrival rate of defects per unit time, k_f.
- Failure rate λ (1/MTBF).

Downtime due to inspection, d is the amount of time, on average, an inspection will take to complete and return the equipment to production. The average downtime due to a breakdown and subsequent repair of the equipment d_b is the time it takes on average to return the equipment to production. The units of both downtime inspection and breakdown repair downtime must be identical but can be measured in hours, days or months depending on the equipment under investigation. The arrival rate of a defect, k_f is the average time a defect arises over a period of time, calculated by the number of defects divided by the total operating time of the equipment under investigation. Failure rate λ is the reciprocal of mean time between failures (MTBF) where MTBF is the mean

operating time between failures of a component or piece of equipment. MTBF, however, should not be confused with the delay-time of a component or piece of equipment. The delay-time is the time from an initial telltale sign of failure to actual failure, both being dependant on the inspection interval, T.

3.3.4 Gather data

The question as to whether a delay-time analysis is carried out using either subjective means or objective means is dependant on what data is available. If maintenance records of inspections carried out with details of failures encountered are available then an objective delay-time analysis can be used to estimate the delay-time. If however this type of data is not available then subjective delay-time analysis must be used. This can be achieved by gathering information from sources such as the maintenance team, operator personnel and management through the use of questionnaires. It has been previously suggested (Christer and Waller (1984)) that the number of experts to use is in the region of 3 to 5 for subjective delay-time analysis. The consistency of the data is another aspect to consider when gathering data. There could be several sources of data available for a piece of equipment giving different signals regarding completeness and accuracy of data which could develop into a time consuming activity to sort the valid data from the irrelevant data.

3.3.5 Objective data analysis

As previously discussed objective delay-time analysis requires maintenance data as well as failure and inspection data in order to estimate the values of the parameters that will indicate the arrival rate of a defect k_f and the delay-time distribution.

3.3.6 Subjective data analysis

It has been documented (Christer et al. (1998b)) that the delay-time concept is not as straightforward to understand by engineers and operators as first imagined during the study of equipment at a company, therefore care needs to be taken when developing questionnaires or interrogating inspection data. To help avoid confusion when trying to implement a delay-time analysis to a manufacturing environment the term 'how long ago' (HLA) and 'how much longer' (HML) can be used (Leung and Kit-leung (1996)). The term HLA is a means of establishing from an engineer or a technician how long ago the fault could have been detected. The problem with asking for an estimate for HLA is that possible blame could be levelled at the individual for not identifying the hidden fault at an earlier inspection, therefore care needs to be taken and trust gained when establishing HLA and HML figures. The delay-time h can be calculated by adding the HLA and HML together. It is prudent to gather data that is not an exact point of time but 3 points of time namely a pessimistic, an optimistic and a most likely figure, thus taking both the pessimistic and optimistic data and calculating an average of both from each expert and comparing it to the most likely figure.

3.3.7 Advantages and disadvantages

There are several advantages and disadvantages for using the subjective delay-time analysis method for estimating a delay-time for plant or equipment. The main advantage with subjective delay-time analysis is that limited failure data is required in order to establish a delay-time estimate, one simply relies on the expertise of the personnel involved with the running of the equipment. Moreover, if the majority of maintenance and inspection data existing is unusable, then a means of establishing figures for the required parameters needs to be established even for objective delay-time analysis. There are however some disadvantages with this method, one disadvantage being that if a lack of faults or failures of the

equipment in question is infrequent then it may take some time to gather enough data for subjective delay-time analysis to be viable. A second disadvantage is that it can be time consuming. It takes time to compile and issue the questionnaire to ensure that all staff involved in the process has an understanding of the delay-time concept. Understanding the delay-time concept has previously proved a tough challenge, therefore the content of the questionnaire is of vital importance in order to avoid lengthy sessions with relevant experts explaining the questionnaire or gathering inaccurate data. In addition to establishing HLA and HML figures there are other questions that need to be addressed, namely:

1. How many failures do you experience each working day/week/month?
2. What is the average downtime for each failure?
3. How many faults have been identified at each inspection?
4. Please give a brief description of the failure and fault.
5. Is the failure or fault preventable?
6. If the failure or fault is preventable, briefly describe how.

3.3.8 Validation of the delay-times and the distribution

An important process in validating the information gathered is to confirm the results from each questionnaire with the author of the questionnaire, this makes certain that the perception of the questionnaires is that of the author of the questionnaire and no misinterpretation has been made (Christer et al. (1998b)). Once the delay-time estimates have been gathered a histogram can be constructed in order to establish the distribution and hence the type of distribution to use. The exponential distribution is frequently used to model the time interval between successive random events and generally used for breakdown repair data. Alternatively, when the failure probability varies over time, the Weibull distribution is appropriate (Pillay and Wang (2003)). It is necessary to test the distribution to the data in question; this can be done by using a chi-square

goodness of fit test. This is achieved by fitting the observed distribution to a theoretical distribution and comparing the frequencies observed in the data to the expected frequencies of the theoretical distribution. Once the model *b(T)*, the probability of a defect arising within a certain time frame as a failure, has been developed then a means of validating it is required in order to give a reasonable amount of confidence to the model. A means of achieving this could be to take a point on the delay-time model, for example 7 days, and using maintenance data of the previous 7 days and comparing the two figures.

3.3.9 Establish assumptions

In order to apply the data to a model there are a number of assumptions that need to be established. The assumptions are generally based on the observations of the data, knowledge of the equipment involved and discussions with the maintenance management team, engineers and operatives. The following are typical assumptions of a simple delay-time model.

1. Inspections take place at regular intervals.
2. Inspections are perfect and that all defects will be identified at inspection.
3. Defects found at inspection will be repaired during the period of inspection.
4. Defects arise at a constant rate λ per unit time.
5. The equipment or machine is in a steady state condition.
6. Defects or failure can only take place when the equipment is in operation.
7. Defects are assumed to arise independently of each other.

Several of the above assumption may appear to be obvious but it is worth having total agreement with all persons involved in the study as even the simplest of assumptions could be misinterpreted or ignored because it may seem unimportant. An example of a simple assumption being ignored or amended

whilst a study is in progress is that of assumption 1, the time interval between inspections. An inspection may be carried out early due to a window of opportunity that has arisen or delayed because of production demands, therefore careful consideration and understanding of the assumptions is vital to the success of any study. Assumption 2 may seem impractical in reality because of the difficulty of knowing whether a fault may have already been present but not evident at an inspection. An inspection can be given a probability of a fault being detected at inspection (Christer et al. (1995)), this is generally given by r, therefore the probability of a perfect inspection is 1-r. For most cases though perfect inspection is assumed as this eases the mathematical complexity for demonstration purposes. Imperfect inspection could be a possible way of adjusting the model to the differing skills and experience of the maintenance staff or if a certain piece of equipment has a history of troublesome inspection repair giving a low utilisation, care is needed however as this type of problem is frequently an engineering issue. For example, a maintenance engineer with 20 years experience is to be replaced by a newly qualified maintenance engineer of 2 years experience. The newly qualified engineer will not have the same knowledge or experience of the equipment and therefore a probability ranging from 0 to 1 could be applied. Similarly a poor track record of inspection repairs and breakdown repairs could be factored into the model. The arrival rate of defects being constant λ, also known as homogeneous Poisson process (HPP) is a deciding factor of the use of the exponential distribution function.

3.3.10 Establish a downtime model D(T), cost model C(T) and environmental model E(T)

When the probability distribution function of a delay-time $f(h)$ follows an exponential distribution, i.e. when the failure rate λ or 1/MTBF is constant over a specified time period, the distribution function, as shown in Equation (3.1), is used to calculate the probability of a defect arising $b(T)$ (Christer and Waller

(1984)):

$$f(h) = \lambda e^{-\lambda h} \tag{3.1}$$

The probability of a defect leading to a breakdown failure *b(T)* can be expressed as follows in Equation (3.2).

$$b(T) = \int_0^T \left(\frac{T-h}{T}\right) f(h)dh \tag{3.2}$$

Combining the distribution function *f(h)* with the breakdown failure probability *b(T)* gives:

$$b(T) = \int_0^T \left(\frac{T-h}{T}\right) \lambda e^{-\lambda h} dh \tag{3.3}$$

This term can be further simplified as:

$$b(T) = \frac{1}{T} \int_0^T (T-h) \lambda e^{-\lambda h} dh \tag{3.4}$$

It is important to note that $b(T)$ is dependant on the delay-time h.

3.3.10.1 Downtime model D(T)

It has been demonstrated (Leung and Kit-leung (1996), Pillay et al. (2001)) that with establishing a probability for breakdown failure *b(T)* it is also possible to establish an expected downtime per unit time function *D(T)* as shown in Equation (3.5).

$$D(T) = \left\{ \frac{d + k_f T b(T) d_b}{T + d} \right\} \tag{3.5}$$

where:

d = Downtime due to inspection.

k_f = Arrival rate of defects per unit time.

$b(T)$ = Probability of a defect arising.

d_b = Average downtime for a breakdown repair.

T = Inspection period.

Substituting $b(T)$ from Equation (3.4) into Equation (3.5) gives:

$$D(T) = \left\{ \frac{d + k_f T \left[\frac{1}{T} \int_0^T (T - h) \lambda e^{-\lambda h} dh \right] d_b}{T + d} \right\} \tag{3.6}$$

3.3.10.2 Cost model C(T)

Similarly, given the cost of inspection $Cost_i$, the cost of a breakdown C_B and the cost of inspection repair C_{IR}, the expected cost per unit time of maintenance of the equipment with an inspection of period T is $C(T)$, giving Equation (3.7) (Pillay et al. (2001)):

$$C(T) = \frac{\left[k_f T \left\{ Cost_B b(T) + Cost_{IR} \left[1 - b(T) \right] \right\} + Cost_i \right]}{(T + d)} \tag{3.7}$$

where:

$C(T)$ = The expected cost per unit time of maintaining the equipment on an inspection schedule of period of time T.

$Cost_B$ = Breakdown repair cost.

$Cost_{IR}$ = Inspection repair cost.

$Cost_i$ = Inspection cost.

The cost of an inspection is simply made up of the cost per hour of the inspection personnel plus the cost per hour of downtime of equipment that may be required in order for the inspection to take place multiplied by the amount of time on average of the inspection, as shown in Equation (3.8) (Jones et al. (2009)).

$$Cost_i = (Cost_{ip} + Cost_d)\ T_{insp} \tag{3.8}$$

where:

$Cost_{ip}$ = Cost of inspection personnel per hour.

$Cost_d$ = Cost of downtime per hour.

T_{insp} = Time taken to inspect.

The cost of a breakdown is calculated as the cost of the failure plus the costs of corrective action to bring the equipment back to a working condition. This is calculated as the cost of the maintenance staff per hour plus the cost of downtime per hour multiplied by the time taken to inspect plus spares used and any special equipment or personnel needed. The details of a breakdown repair are shown in Equation (3.9) (Jones et al. (2009)).

$$Cost_B = (M_{staff} + Cost_d)\ (T_{insp} + T_{repair}) + S_p + S_e \tag{3.9}$$

where:

M_{staff} = Maintenance staff cost per hour.

T_{repair} = Time taken to repair.

S_p = Spares and replacement parts cost.

S_e = Special equipment / personnel / hire costs.

The cost of an inspection repair is somewhat identical to the breakdown repair cost apart from the following:

- Inspection repair will not generally have equipment hire costs (S_e).
- The time to repair will be of shorter duration for inspection repair.

The time for an inspection repair having a shorter duration is mainly due to a breakdown having a greater knock-on effect. An example of a breakdown repair having a greater knock-on effect than an inspection repair could be the timing belt from an engine. An inspection repair would entail inspecting and replacing the item multiplied by the time it would take plus the cost of the item. A breakdown repair of a timing belt will be the same as an inspection repair plus the cost of pistons, a cylinder head and crankshaft multiplied by the time to repair, obviously greater in duration. The equation for inspection repair is shown in Equation (3.10) (Jones et al. (2009)).

$$Cost_{IR} = (M_{staff} + Cost_d)\,(T_{insp} + T_{repair}) + S_p \tag{3.10}$$

A point to note regarding the cost model C(T) (Equation (3.7)) is that it describes a worst case scenario. This worst case scenario is a fault leading to failure before an inspection takes place or a fault being detected at inspection. Conversely, a best case scenario would be no failure taking place before inspection and no fault being present at inspection. A development for this cost model could be establishing a compromise between a best case scenario and a worst case scenario, this area of research though is outside the scope of this chapter.

3.3.10.3 Environmental model E(T)

The aim of the environmental model is to establish parameters relating to the impact of a failure of a piece of equipment or a part of a process on the environment. Often in industry a failure of a machine or a piece of equipment is generally detrimental to production, the only impact being that production will cease for several hours with a cost relating to the lost production and the cost of repair. When attempting to gauge the impact on the environment of a failure a judgement has to be made as to the danger to the public as well as the environment costs. Environmental accidents can be simple spillages but can also be severe enough to have grave consequences both to life as well as damaging the environment for many years. Often this type of accident is difficult if not impossible to reverse, compounding the importance of avoiding equipment or component failures. An environmental model relating to the above concerns is shown in Equation (3.11) (Jones et al. (2009)).

$$E(T) = \frac{k_f T\left\{E_{impact} b(T) + E_{damage}\left[1 - b(T)\right]\right\}}{(T + d)} \tag{3.11}$$

where:

$$E_{impact} = E_{health} + E_{collateral} + E_{reverse} \tag{3.12}$$

The term E_{health} gives a measure of the possible consequences a failure might have to human health. The term takes into account the severity of injury, the number of people affected and the probability of the accident resulting in injury. E_{health} is illustrated in Equation (3.13). It is important to highlight that the probability for each term is a probability of a certain consequence taking place given a failure, not the probability of a failure taking place. For example, should an oil platform explode then there is a high probability that injuries will be encountered and lives will be lost. The point of this probability is to attempt to give an indication as to

the possible extent, in human terms, should failure occur. This probability is known as a conditional probability or failure consequence probability.

$$E_{health} = CL_1.P_1 + CL_2.P_2 + CL_3.P_3 + CL_4.P_4 + CL_5.P_5 \qquad (3.13)$$

where:

CL_1 = $Cost_{h1}.Life_{h1}$

CL_2 = $Cost_{h2}.Life_{h2}$

CL_3 = $Cost_{h3}.Life_{h3}$

CL_4 = $Cost_{h4}.Life_{h4}$

CL_5 = $Cost_{h5}.Life_{h5}$

$Cost_{h1}$ = Cost of unwell.

$Cost_{h2}$ = Cost of ill health.

$Cost_{h3}$ = Cost of hospitalisation.

$Cost_{h4}$ = Cost of disability.

$Cost_{h5}$ = Cost of a life.

$Life_{hn}$ = Number of people effected.

P_n = Conditional probability of particular event.

The term $E_{collateral}$ gives a measure of the possible consequences a failure might have to plant items and to any residential buildings. The term takes into account the possible costs incurred and the probability of the accident resulting in damage. $E_{collateral}$ is illustrated in Equation (3.14).

$$E_{collateral} = (cost_{plant}\, P_{plant}) + (cost_{Res}\, P_{res}) \qquad (3.14)$$

where:

$cost_{plant}$ = Cost of plant items damaged.

$cost_{Res}$ = Cost of residential building damaged.

P_{plant} = Probability of plant item damage.

P_{res} = Probability of residential building damage.

The term E_{damage} gives a measure of the possible consequences a failure might have to the environment. The term takes into account the cost to clean up any spillage that may result from a failure and the probability of a failure resulting in spillage requiring clean up. E_{damage} is illustrated in Equation (3.15).

$$E_{damage} = cost_{clean}\, P_{clean} \tag{3.15}$$

where:

$cost_{clean}$ = Cost to clean up.

P_{clean} = Probability of spillage.

Another factor to consider when establishing an environmental model is whether the result of a failure is reversible i.e. if it is possible to reverse or clean up the damage the failure has caused. With the possibility to reverse the effects of a failure a suitable time scale needs to be applied together with a factor relating to the amount of time. Table 3.1 illustrates a range of time scales for the amount of time the reversal or clean up time will take following a failure resulting in spillage. A brief review of several industrial accidents from differing industries which resulted in environmental damage requiring clean up forms the basis of table 3.1. Having previously established a measure of the possible consequences failure might have to the environment through the term E_{damage}, the review took into account possible timescales required. Additional to the clean up time is a factor relating to each time scale, this factor increases as the amount of time to

reverse the failure increases. There is a rank of 'low' given to the first 3 factors, a rank of 'medium' to the next 3 factors, a rank of 'high' to the next 2 factors and a rank of 'very high' to the remaining 2 factors. The rank of 'medium', 'high' and 'very high' signifies a considerable environmental disaster.

Table 3.1. Factor relating to the time taken to clean up a failure.

Clean-up time	*Factor*	*Rank*
0 to 4 weeks	0.1	Low
1 to 3 months	0.2	
3 to 12 months	0.3	
1 to 3 years	0.4	Medium
3 to 7 years	0.5	
7 to 10 years	0.6	
10 to 25 years	0.7	High
25 to 50 years	0.8	
50 to 100 years	0.9	Very high
100 + years	1	

A reversal probability is an effective way to quantify the possible irreversibility of a failure leading to an environmental accident, illustrated in Equation (3.16).

$$E_{reverse} = \frac{E_{damage}}{(1 - F_r)} \tag{3.16}$$

where:

F_r = Factor relating to the clean up time.

It is important to highlight in Equation (3.16) that if the reversal period of time is 100+ years i.e. when F_r is 1, then it is taken as an infinite amount of time. This amount of time is impractical to model as it is obviously a serious failure and

outside the scope of this model. Given this information a calculation can now be made as to the environmental impact of a possible failure given the above parameters and applying them to Equation (3.11).

3.4 Case study

In order to demonstrate the above models for downtime *D(T)*, cost *C(T)* and environmental *E(T)* a case study of a factory producing carbon black in the UK is given.

This particular process of creating carbon black is made up of three units A, C and D. The three units cover the whole process stream from the reactor to the MUF (Main Unit Filter), this collects and separates the product from the gasses produced. The carbon black is then transferred into storage containers. A low pressure air and natural gas produce a flame of high temperature (1500 degrees centigrade) in the combustion zone of the reactor. Heavy oil, which is known as feedstock, is sprayed into the flame and a carbon black reaction occurs. After the feedstock is exposed to the high temperature it is quenched with water in order to stop the carbon black formation reaction. At this point the basic form of carbon black is formed, carbon black powder. Each unit consists of either 7 or 9 compartments each housing 205 filters:

- Unit A is made up of 7 compartments housing 205 filters per compartment, giving a total of 1,435 filters.
- Unit C is made up of 9 compartments housing 205 filters per compartment, giving a total of 1,845.
- Unit D is again made up of 7 compartments housing 205 filters per compartment, giving a total of 1,435.

The filter is a bag type filter measuring approximately 10cm in diameter and 2.5m in length. The cost of a filter is around £28 each with a life expectancy of three to four years. There is a second manufacturer of the filter that has a cost of around £7.50 but it has a life expectancy of 12 to 14 months with a lower tolerance to acid than the more expensive filter. A typical carbon black process is shown in figure 3.2.

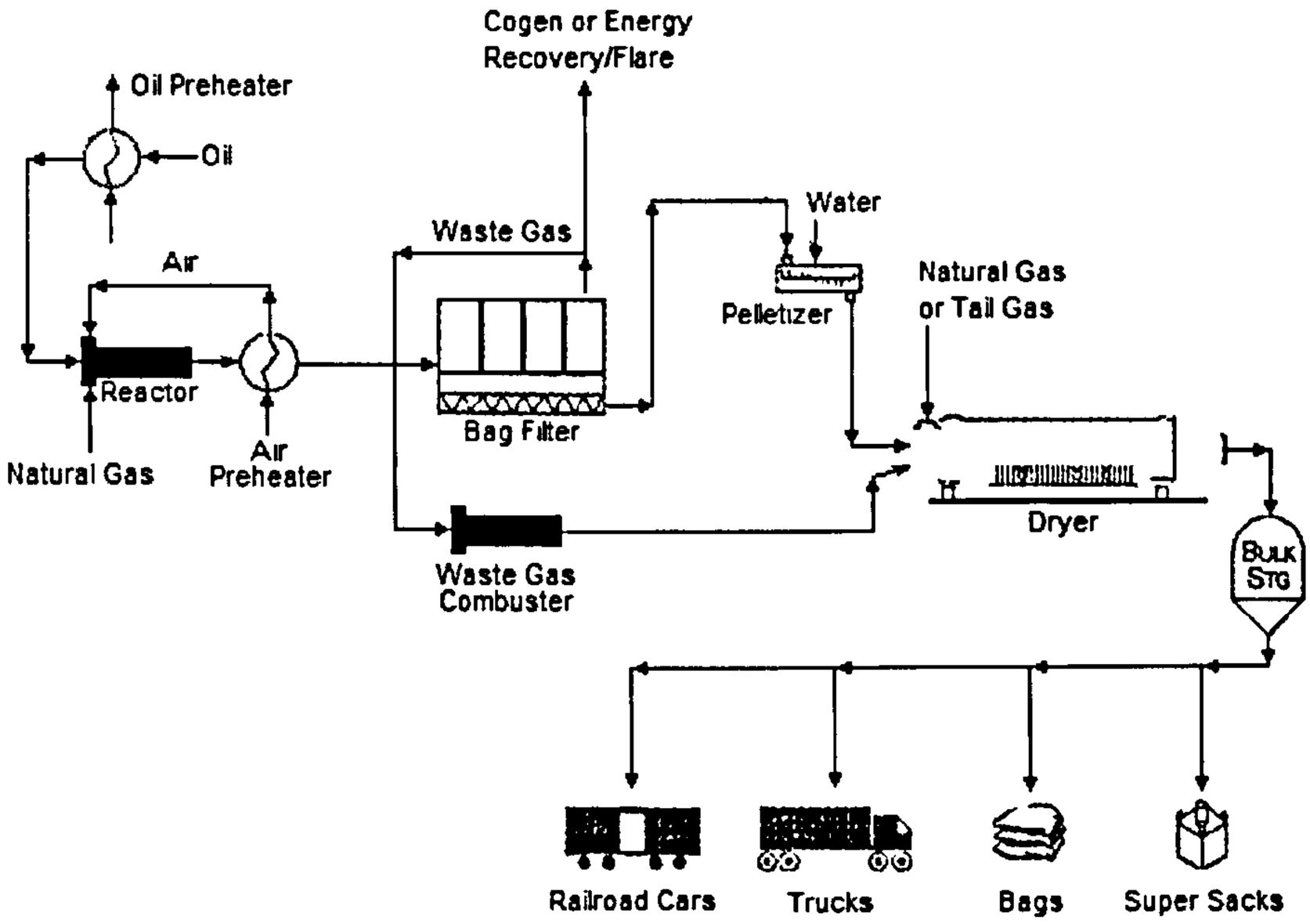


Figure 3.2. A typical carbon-black process diagram.

3.4.1 Failure of a filter bag

This study will examine the failure of a filter bag as it is a primary concern relating to the release of carbon black into the atmosphere. The consequences of a failure of a filter bag can result in carbon black being leaked into the atmosphere. Because the particles when in the 'fluffy' state are so fine, it is estimated that one tablespoon of carbon black could cover an estimated 4000m^2 in this fine powder state. Carbon black has been classified by the International Agency for Research

on Cancer (IARC) as a group 2B carcinogen (The environmental protection act (1990)), this means that it is a possible carcinogenic to humans based on sufficient evidence in animals and insufficient evidence in humans, although morality studies have shown no association between carbon black and lung cancer rates. Studies have also demonstrated that regular exposure can result in a reduction in lung capacity. Inhalation of the dust causes coughing and wheezing, can cause drying to the skin with repeated and prolonged contact. Carbon black is not biodegradable but is non-toxic, often disposed of in a landfill because it will not seep or release any constituents to the groundwater (ICBA (2004)). Given this information the environmental impact of a leakage is considerable. The environmental agency has the power to suspend or even close production of the site should it consider it a hazard to the public and environment (IPPC (2007)).

3.4.2 Costs of failure of a filter bag

When a filter bag is to be changed the compartment has to be closed down. This requires 8 hours of cool down followed by a period between 6 and 24 hours downtime for repair and replacement then a further 2 hours to warm the unit back up. If a total re-bag is required downtime is generally around 7 days. When a unit is brought off-line it continues to burn gasses in order to keep the temperature in the reactor constant thus wasting energy. Additionally, the system allows that any surplus energy created during the manufacturing process can be sold back to the national grid. The cost of a failure is therefore compounded not only due to the costs in respect of the energy wasted but the loss of potential income from any surplus energy generated. Sometimes specialist maintenance crews need to be brought in to deal with a particular breakdown and failure, adding to the overall costs. A typical example of a breakdown which took 7 days to repair and replace all bags is demonstrated below.

- Loss of production per hour: £1,500
- Burn of gasses per hour: £238

- Loss of export of energy per hour: £26
- Cost of maintenance personnel per hour: £28
- Cost of supervisor per hour: £36
- Cost of replacement filters (205): £40,180
- Jetting crew: £710
- Jetter hire: £300
- Cherry picker hire: £2,500

This gives a total cost for a breakdown resulting in 1,435 filters being replaced effecting 1 MUF for a period of 7 days to be £350,794.

3.4.3 Establishing a delay-time analysis

In order to establish a delay-time analysis for this example several parameters need to be known. In this facility there are 205 filter bags in each compartment with either 7 or 9 compartments in each MUF. Due to the number of bags in each MUF in total this system is regarded as a system with multiple components. The parameters used in this example are as follows:

- The arrival rate of a defect, k_f - 0.28 per day.
- Mean time between failure (MTBF) - 3 years.
- Downtime for an inspection, d - 0.1 days.
- Downtime for breakdown repair, d_b - 7 days.
- Breakdown repair cost, $Cost_B$ - £350,974.
- Inspection repair cost, $Cost_{IR}$ - £5,000.
- Inspection cost, $Cost_i$ - £67.

The data has been gathered from maintenance and inspection records over a period of 12 months (appendix 3). With the system being regarded as a multiple

component system, that is repairable with failures following a Poisson process i.e. arriving randomly, an exponential distribution is used together with a MTBF and arrival rate of a defect. The arrival rate of a defect k_f was established by looking at the total number of defects for all three units for 1 year and finding an average of 0.28 per day. The MTBF parameter of 3 years is the average time between a failure leading to a release of carbon black into the atmosphere. An inspection can either be a visual inspection checking the colour of the flame at the reactor or it can be what is called a 'cloth check' which takes a sample of the air coming out into the atmosphere, this test takes between 10 minutes and 15 minutes to carry out. Both the visual inspection and cloth check inspection does not require a stop to production. However, an inspection to physically check the condition of the filter bags takes around 2.5 hours in duration. A total re-bag of a unit takes around 7 days to complete including cool down and heat up periods. Having established the relevant parameters it is now possible to apply them to Equation (3.6). Applying the parameters to Equation (3.6) it is possible to establish an inspection interval where a minimum downtime is of primary concern as illustrated in figure 3.3.

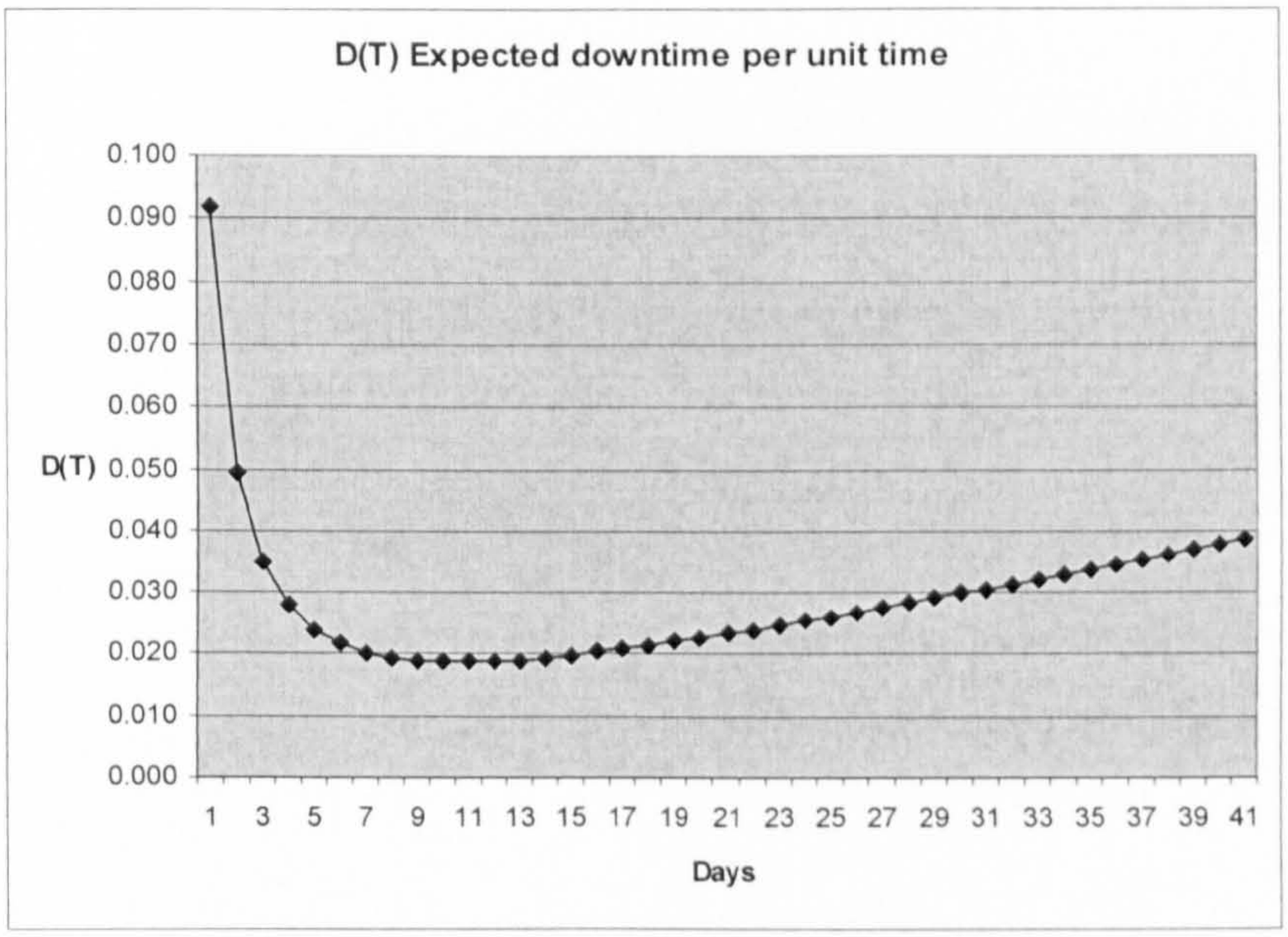


Figure 3.3. Optimal inspection period based on minimum downtime D(T).

As illustrated in figure 3.3, the minimum inspection interval based on minimum downtime D(T) is 11 days. Applying the cost parameters to Equation (3.7) an optimal inspection interval can be established. From the obtained result, the downtime curve (D(T) can be drawn against t (days) as shown in figure 3.3. Using methods such as the 'best fit' technique, the mathematical function of D(T) can be obtained. The minimum D(T) value can be found when d(D(T))/dt = 0. However, in this case where it is not difficult to find the minimum D(T) value from the graph and also a very high level of accuracy is not really necessary, a time consuming process of finding the minimum D(T) value accurately described above is not used. Instead the minimum D(T) value is directly found by observing the D(T) curve from the graph in figure 3.3. This principle is applied to establish C(T) and E(T).

When the cost C(T) is of primary concern the optimum inspection interval is 11 days with a cost of £940 as shown in figure 3.4.

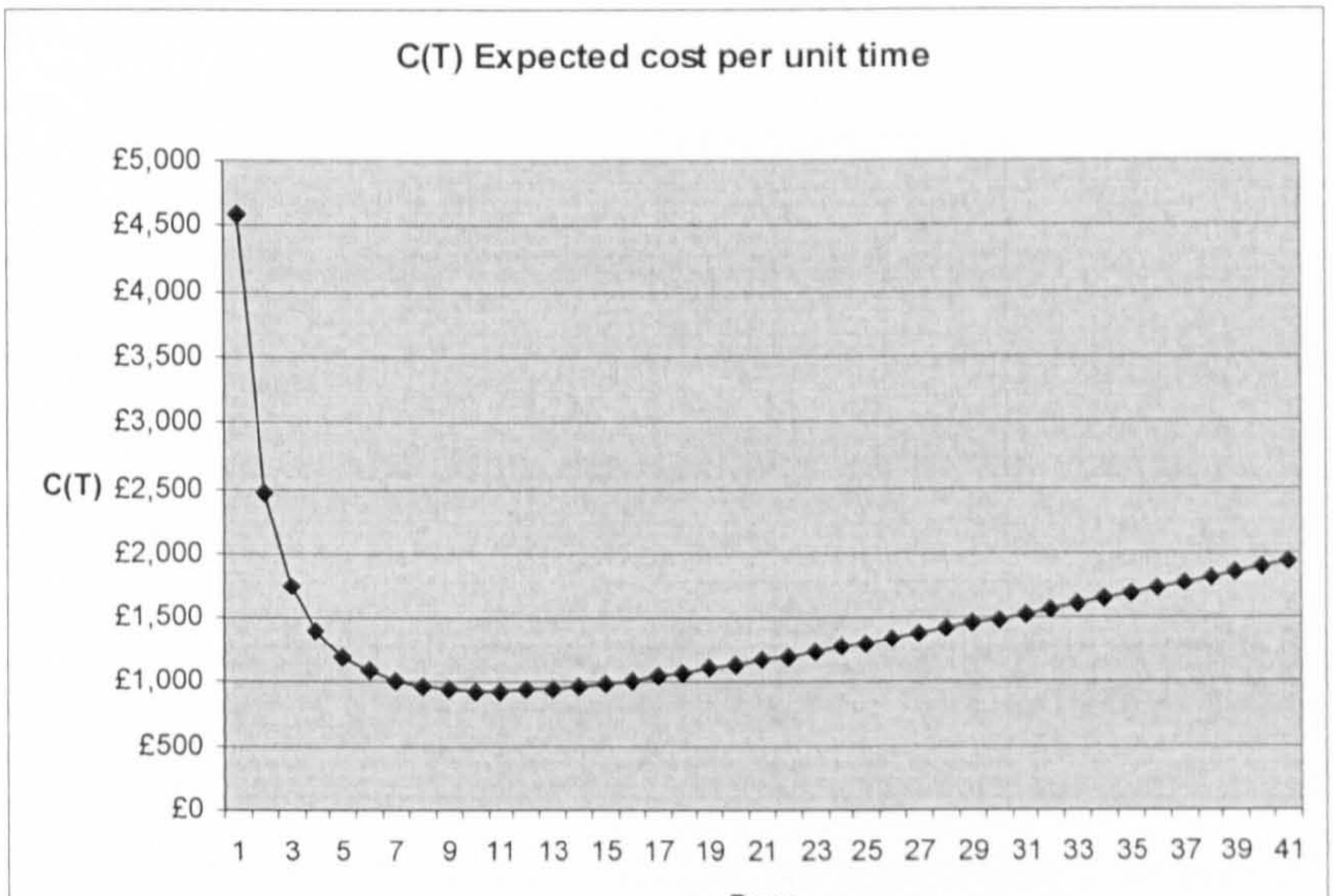


Figure 3.4. Optimal inspection period based on minimum cost C(T).

With the minimum downtime D(T) being 11 days and minimum downtime cost C(T) being 11 days an inspection interval is clearly straightforward. By applying the environmental parameters, illustrated in table 3.2, to Equation (3.11), it is possible to establish an optimal inspection interval based on minimising the environmental impact should failure occur.

Table 3.2. Environmental parameters to establish environmental model E(T).

Model Parameters		*Cost*	*Probability*	*Calculated Cost*
Environmental Human	Sickness	£10k	0.5	£5k
	Ill health	£0	0	£0
	Hospitalisation	£0	0	£0
	Disability	£0	0	£0
	Loss of life	£0	0	£0
			Total	£5k
Environmental Collateral	Plant	£250k	1	£250k
	Residential	£250k	0.5	£125k
			Total	£375k
Environmental Damage	(factor 0.2)	£200k	1	£200k
Environmental Reverse		£250k	1	£250k
Environmental Impact			*Total*	£630k

The probabilities illustrated in table 3.2 relate to the fact that should a failure occur leading to carbon black being released into the atmosphere then there is a probability of 1 that the plant will be damaged and this will result in damage costing £250,000. This principle applies to the other probabilities in table 3.2, for example, there is a 0.5 probability of residential damage should a release occur. Utilising the above parameters and applying them to Equation (3.11) and table 3.1, an environmental criticality can be established. An inspection interval of 11 days with an estimated cost of £27,641 has been established as shown in figure 3.5.

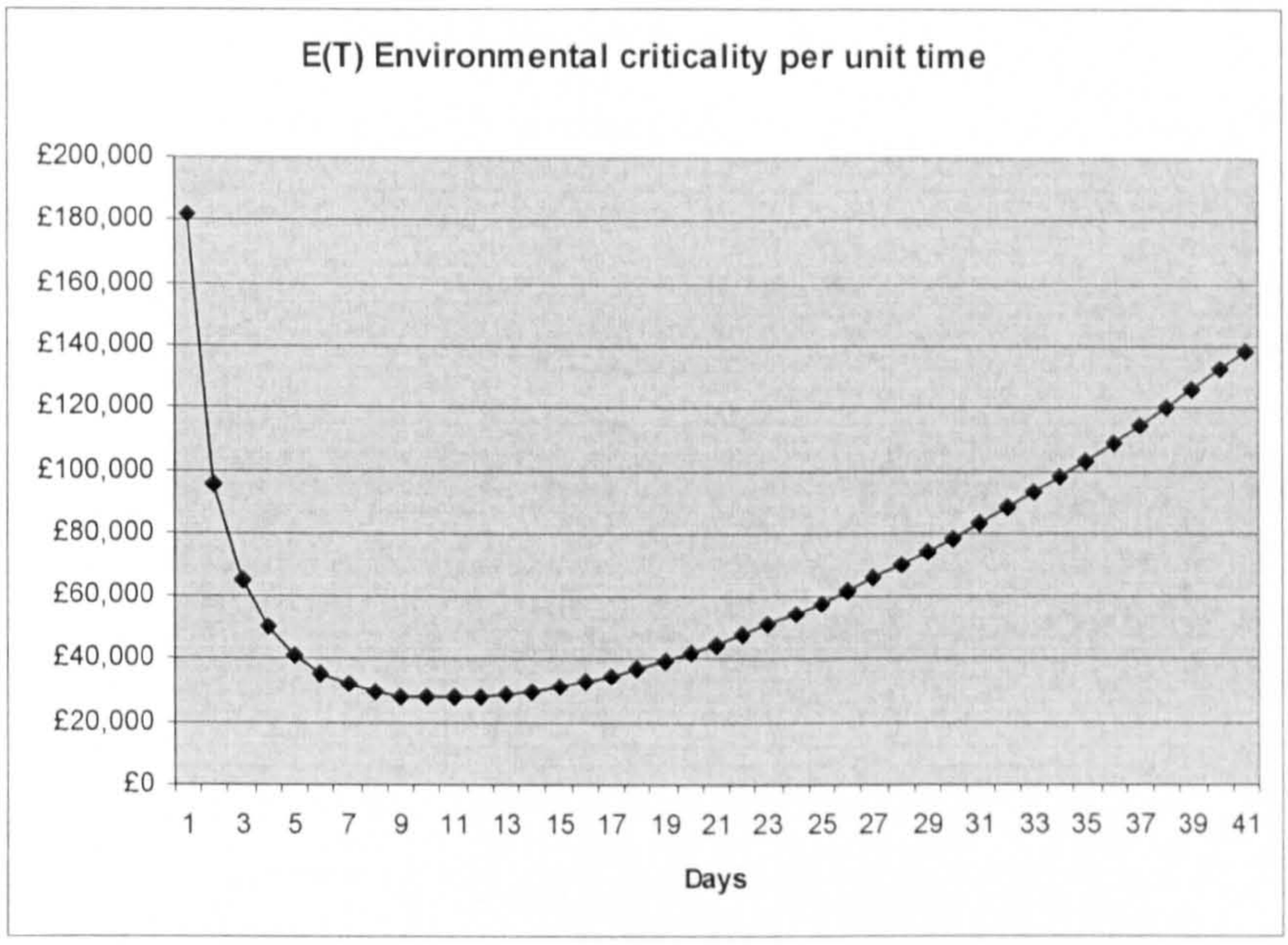


Figure 3.5. Optimal inspection period based on minimum cost to the environment E(T).

3.4.4 Validation

In order to analyse the effect of change to the results of D(T), C(T) and E(T) a sensitivity analysis was carried out on each model. The analysis varied certain input data by 5% and 10% resulting in the following.

3.4.4.1 Validation of D(T)

The sensitivity analysis was carried out on the variables k_f (arrival rate of defects) and λ (failure rate) with an increase and decrease of 5% and 10% on each variable. The following five cases were considered.

Case 1: Variables k_f and λ decrease by 10%

Case 2: Variables k_f and λ decrease by 5%

Case 3: Variables k_f and λ unchanged

Case 4: Variables k_f and λ increase by 5%

Case 5: Variables k_f and λ increase by 10%

The increase and decrease of variables resulted in small changes in variation to the downtime D(T) and inspection interval as illustrated in table 3.3.

Table 3.3. Sensitivity analysis of increasing and decreasing k_f and λ.

	Downtime D(T)	Inspection interval
Case 1	26 minutes	11 days
Case 2	26 minutes	11 days
Case 3	27 minutes	11 days
Case 4	28 minutes	10 days
Case 5	28 minutes	10 days

The optimal inspection interval remains very close to the original interval given an increase and decrease of 5% and 10%. The sensitivity analysis for D(T) is shown graphically in figure 3.6.

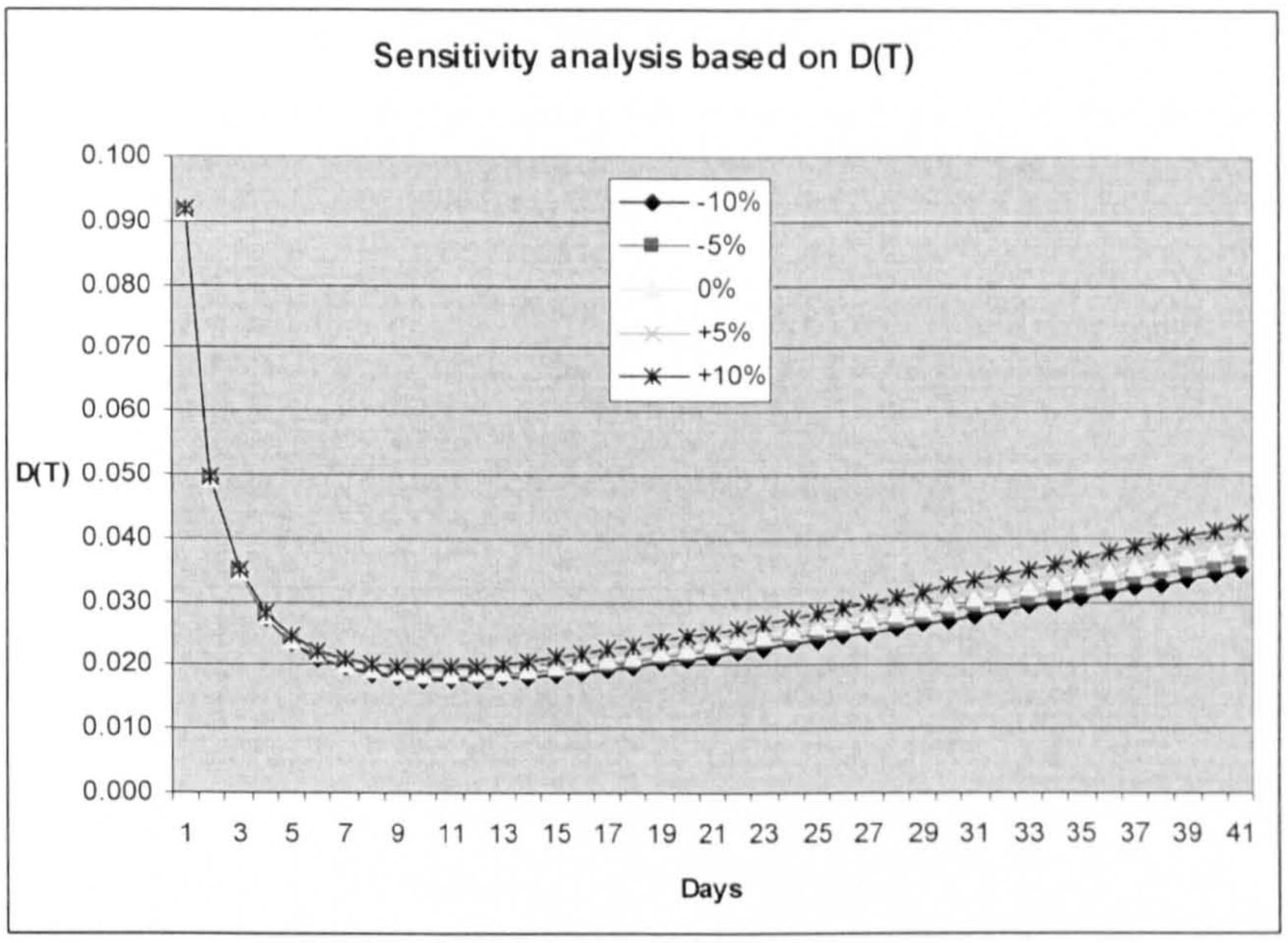


Figure 3.6. A graphical representation of the sensitivity analysis from table 3.3.

3.4.4.2 Validation of C(T)

A sensitivity analysis was carried out on the cost of an inspection repair and the cost of an inspection in order to analyse the effect of a change in the costs. The cost of an inspection repair and an inspection has been increased and decreased by 5% and 10%. Similarly to validation of D(T) the following five cases were considered.

Case 1: $Cost_{IR}$ and $Cost_i$ decrease by 10%

Case 2: $Cost_{IR}$ and $Cost_i$ decrease by 5%

Case 3: $Cost_{IR}$ and $Cost_i$ unchanged

Case 4: $Cost_{IR}$ and $Cost_i$ increase by 5%

Case 5: $Cost_{IR}$ and $Cost_i$ increase by 10%

The result of this analysis is that a decrease in inspection repair costs and

inspection costs results in a slight reduction in the inspection interval as well as the cost C(T). Conversely, as the costs of inspection repair and inspection increase then the cost C(T) increases, the inspection interval remains 11 days. The result of this analysis is shown in table 3.4.

Table 3.4. Sensitivity analysis of increasing and decreasing cost C(T).

	Cost C(T)	Inspection interval
Case 1	£891	10 days
Case 2	£916	10 days
Case 3	£940	11 days
Case 4	£963	11 days
Case 5	£986	11 days

The sensitivity analysis is also shown graphically in figure 3.7. The optimal inspection interval remains very close to the original interval given an increase and decrease of 5% and 10%.

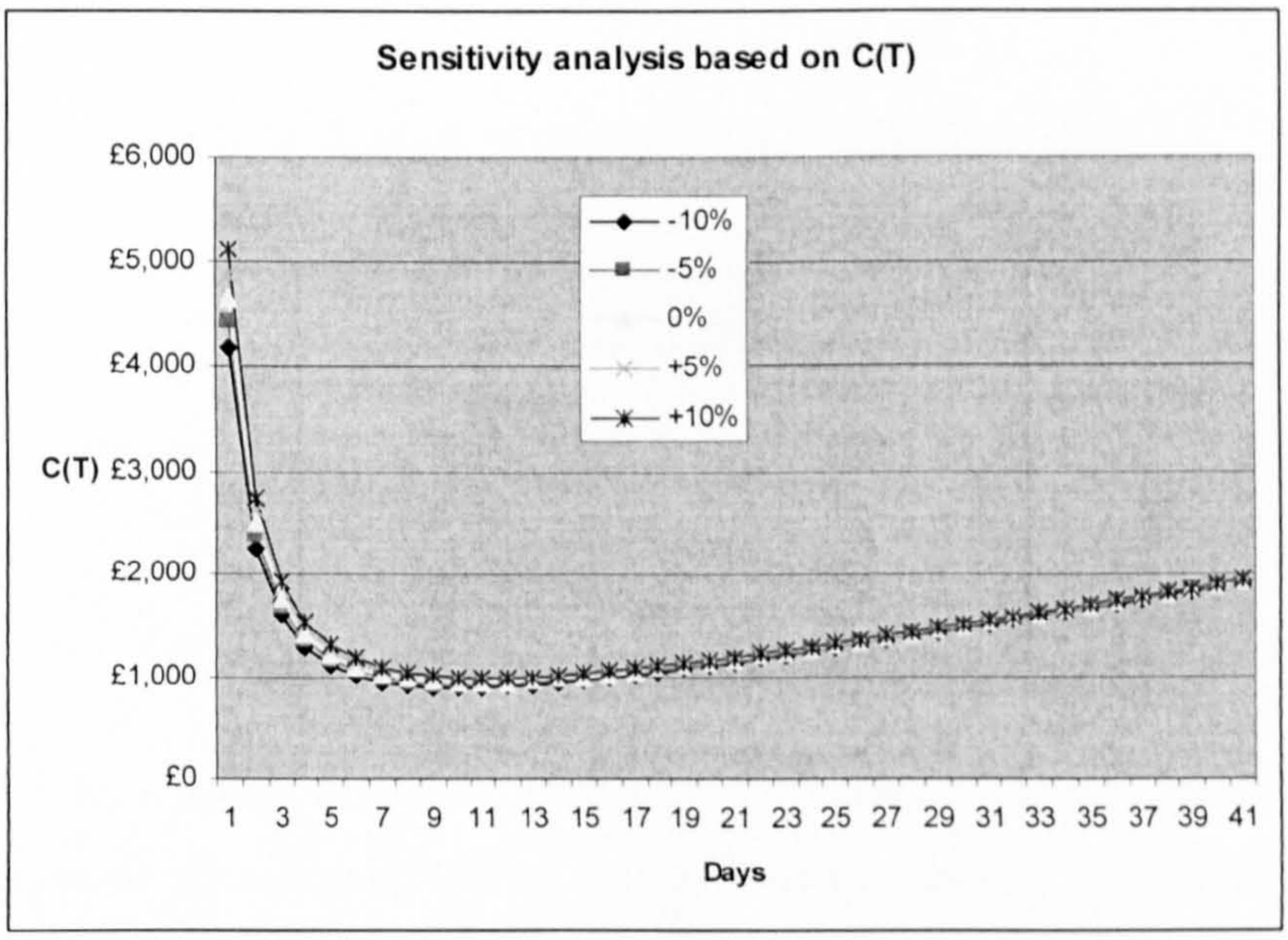


Figure 3.7. A graphical representation of the sensitivity analysis from table 3.4.

3.4.4.3 Validation of E(T)

A sensitivity analysis was carried out on the cost of the environmental impact (E_{impact}) and environmental damage (E_{damage}) analysing the effect on a change in the costs. The cost of E_{impact} and E_{damage} increased and decreased by 5% and 10%. Similarly to D(T) and C(T), the following five cases were considered.

Case 1: E_{impact} and E_{damage} decrease by 10%

Case 2: E_{impact} and E_{damage} decrease by 5%

Case 3: E_{impact} and E_{damage} unchanged

Case 4: E_{impact} and E_{damage} increase by 5%

Case 5: E_{impact} and E_{damage} increase by 10%

The result of this analysis is that a decrease in E_{impact} and E_{damage} results in a slight reduction in cost E(T). As the costs of E_{impact} and E_{damage} increase then the cost E(T) increases, the inspection interval however remains at 12 days. The result of this analysis is shown in table 3.5.

Table 3.5. Sensitivity analysis of increasing and decreasing cost E(T).

	Cost E(T)	Inspection interval
Case 1	£24,877	11 days
Case 2	£26,595	11 days
Case 3	£27,641	11 days
Case 4	£29,023	11 days
Case 5	£30,405	11 days

The sensitivity analysis is shown graphically in figure 3.8. The optimal inspection interval remains unchanged given an increase and decrease of 5% and 10%.

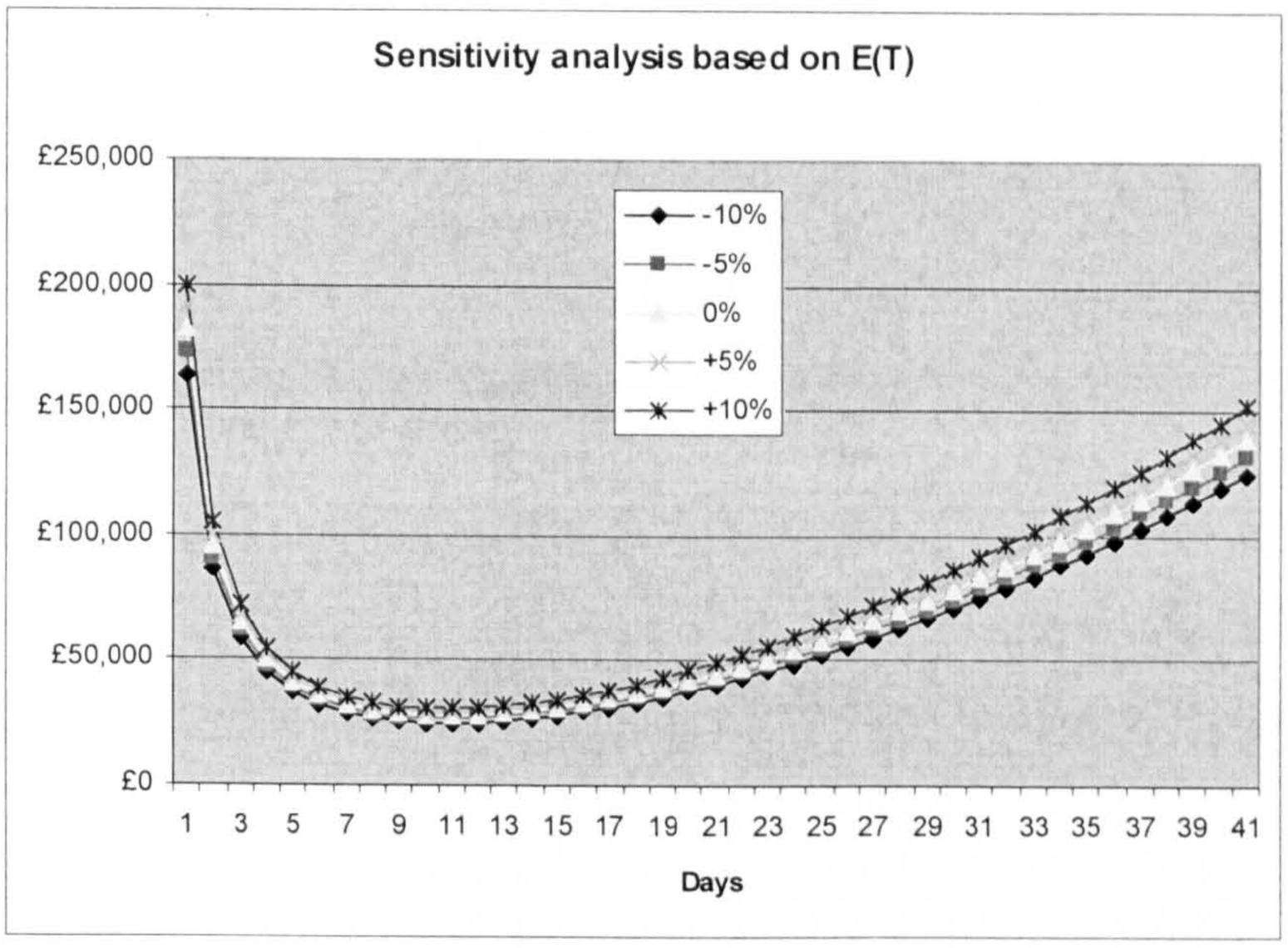


Figure 3.8. A graphical representation of the sensitivity analysis from table 3.5.

3.4.5 Discussion

The decision to focus attention on the filter bags came after a study of faults and repairs data for the whole of last year (2006). When a fault, failure or routine shutdown for maintenance was carried out, discounting any downtime under 5 hours duration, 59% of unit A was attributed to the filter bags whether it was a re-bag or a component associated with a filter bag. The figure for unit C came in lower with a figure of 27% with unit D recording no downtime due to filter bag failure.

It has been demonstrated in this case study that an optimal inspection interval taking into account a minimum downtime D(T) of 11 days has been established using the delay-time analysis technique. Using minimum cost C(T) as the criteria an inspection interval of 11 days with a cost of £940 was calculated. An inspection interval of 11 days when applying the environmental model was

established.

Current practice at the company is that of a weekly inspection interval involving a flame check and a cloth check. It can be argued that this inspection interval could move to a 2 weekly interval but given the nature of the two inspection checks and the fact that it does not stop production, a weekly inspection interval appears reasonable.

3.5 Conclusion

This case study looked at a company in the UK producing carbon black. Carbon black is carcinogenic which carries certain risks to humans, as previously described, given certain levels of exposure. Taking this into account a failure of a filter bag or a component associated with a filter bag could lead to exposure to humans, both on-site and residentially, of carbon black. The risk to human health as a result of inhalation generally points toward temporary breathing difficulties and coughing.

This chapter demonstrates the delay-time concept for the use of minimising downtime and costs, setting inspection intervals to achieve this. The chapter also demonstrates the use of delay-time analysis for a potential environmental catastrophe resulting from failure of a piece of equipment or a component. The environmental model looked at factors such as human loss of life and the impact on the environment. The model also takes into account whether the damage from such a failure is reversible, if so, at what cost. Information was gathered from historical data as well as expert judgement. Parameters were established from this information in order to develop the delay-time models. The delay-time environmental model was applied to the possible release of carbon black, but this model could be equally applied to the oil industry, the chemical industry and to the nuclear industry as it gives a measure of the consequence should a failure lead

to an environmental disaster.

With regard to this case study, the optimal inspection period is a matter for the management team to decide upon. The factors to consider are minimal downtime, minimising cost or minimising the environmental impact should a failure lead to a release of carbon black into the atmosphere. Given the close proximity of all three inspection intervals it should be a relatively straightforward task to establish an inspection interval.

Chapter 4

The use of fuzzy set modelling for maintenance planning in a manufacturing industry

Summary

This chapter has been written to give a standardisation of information for applying delay-time analysis to a maintenance and inspection department. The aim of this chapter is to take both subjective and objective information gathered and elicit the required information using fuzzy set modelling for the purpose of applying it to delay-time analysis. A methodology has been developed and applied to a case study in order to demonstrate the process involved.

4.1 Introduction

Information in a company can come in many forms, either from historical data or from expert judgement or a combination of the two. This information can often be vague, subjective and carry a high degree of uncertainty resulting in a lack of confidence in the data available. This lack of confidence may come under one or more of the following areas:

- Lack of data.
- Vagueness of information.
- Uncertainties in data.
- Incomplete data / information.
- Human judgement.

A lack of data when carrying out any analysis can result in distorted results due to the reliance on an individual's perception and judgement of the data that is lacking. This can result in vagueness of information. Vagueness of information can also come in the form of imprecise instructions or procedures for maintaining a system or machine. This vagueness could then lead to inconsistency with inspections or maintenance tasks to be carried out, leading to interpretation of information using individual judgement. Uncertainties in data will undermine confidence in any analysis, casting doubt over the results. Incomplete data could render a study void before it begins. A common factor which can compound all of the other factors relating to data is that of human judgement. This can vary from individual to individual resulting in inaccurate analysis, uncertainty with the results of the analysis and reduced confidence in the course of action to be taken.

When applying a decision making model to a manufacturing company the information gathered is crucial to the success of the analysis, requiring accuracy and relevance from the start. Often data that is required is available partly from objective historical data but requires the input of additional expert judgement in order to complete the analysis. It is the merging of historical data with expert judgement which can often cast doubt over the accuracy of the results. Combining two different types of data and standardising it into a usable and accurate form in order to apply it to a decision making model, in this case delay-time analysis, is required. This information needs to be elicited in order for it to be usable in any decision making model. A framework for this is illustrated in figure 4.1.

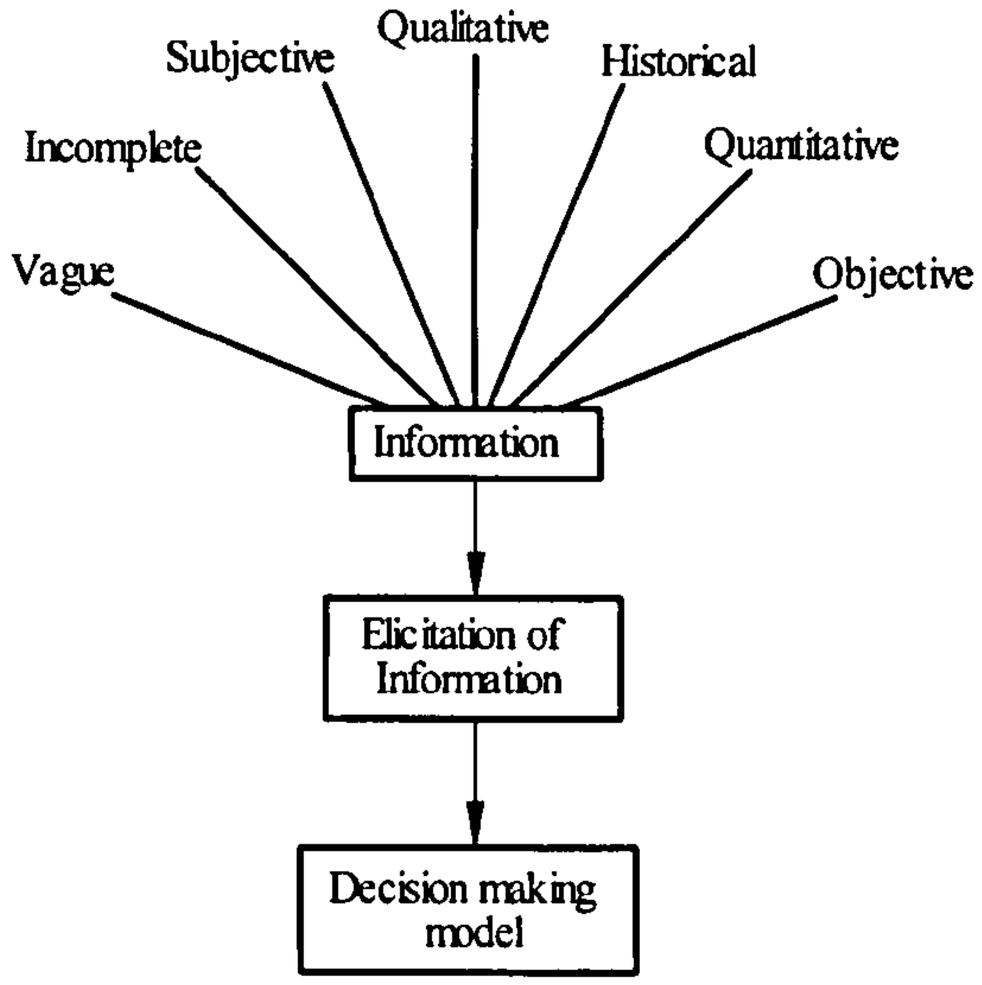


Figure 4.1. A proposed framework for the elicitation of information in a company.

As illustrated in figure 4.1, information may come from many areas of an organisation as well as being in different forms, therefore elicitation of this information is required.

The elicitation of information in this chapter will attempt to combine a number of objective parameters with a number of subjective parameters for the purpose of applying delay-time analysis.

When applying delay-time analysis to any problem, certain parameters need to be established. It is at this point that the accuracy of the data used in establishing the parameters is vital. Delay-time analysis has been used as a tool for reducing the downtime, *D(T)* (Christer et al. (1995)) of a machine or equipment based on an inspection period *T,* given the probability of a defect arising within this time frame *b(T)*. For a particular plant item, component or series of machines, delay-time analysis is useful because the equipment in question is generally high volume and high capital expense, therefore any reduction in downtime due to breakdown or over inspection can be beneficial. As with the modelling of downtime per unit time, it is also possible to establish a cost model, *C(T)* (Leung and Kit-leung

(1996)), again based on an inspection period T and probability $b(T)$. The cost model $C(T)$ estimates the expected cost per unit time of maintaining the equipment. An environmental model $E(T)$ has recently been developed (Jones et al. (2009)) for environmentally sensitive products or processes. It establishes the impact of a failure of a piece of equipment or a part of a process on the environment. Often in industry a failure of a machine or a piece of equipment is generally detrimental to production. The only impact of a failure is that production will cease for several hours with a cost relating to the lost production and the cost of repair. When attempting to gauge the impact on the environment of a failure a judgement has to be made as to the danger to the public as well as the environment costs.

The aim of the environmental model is to establish an inspection interval, given certain parameters, relating to the impact of a failure of a piece of equipment or a part of a process on the environment. Environmental accidents can be in the form of simple spillages but can also be severe enough to have grave consequences both to human life as well as damaging the environment for many years. Often this type of accident is difficult, if not impossible, to reverse thus compounding the importance of avoiding equipment or component failures. The environmental model relating to the above concerns is illustrated in section 3.3.10.3.

The parameters that relate to the environmental model E(T), need to come from historical data as well as expert judgement (subjective data). The problem exists though that either subjective or objective information can only be used separate of each other, not combined together. A detailed definition of the objective data that is required to carry out a delay-time analysis is given in section 3.3.3:

A method of taking subjective information, combining it with any historical data and objective data that may be available and transforming it into useful

parameters for delay-time analysis can be achieved using fuzzy logic. Fuzzy logic allows a gradual transition from one state or linguistic term to another. It permits the use of linguistic terms to describe a system or state, providing flexible modelling of imprecise data and information.

4.2 Applications of fuzzy logic

Fuzzy logic has touched most sectors from risk-based assessment of a fishing vessel (Pillay and Wang (2003)) to the hospitality industry (Petrovic-Lazarevic and Wong (2000)) and from supply chain performance (Lau et al. (2002)) to construction dispute evaluation in the building and construction industry (Cheung et al. (2001)). Its uses also cover the business industry (Wilson and McDonald (1994)) including developing a marketing strategy (Li (2000)) as well as the social sector, notably clinical applications constructing artificial intelligence programs that perform diagnosis and make therapy recommendations (Clancey and Shortliffe (1984)).

Given the wide variety of applications utilising fuzzy logic, this chapter will attempt to look at several relevant papers where similar work has been carried out, namely papers dealing with probability, risk and costs relating to maintenance activities.

The risk assessment using a fuzzy set approach (Pillay and Wang (2003)) looked at the problem of failure data on a typical fishing vessel. The data relating to fishing vessels is generally scarce and any data that is available has a high degree of uncertainty attached to it. This paper, given the problems generally associated with data collection, set about modelling the occurrence likelihood and the possible consequence of hazards established using fuzzy logic. The use of fault tree analysis (FTA) was used to calculate the probability of system failures, establishing the critical events that may lead to failure. Linguistic variables were

then established in order to represent the occurrence likelihood of a critical event. The consequences of a failure, or the severity of the consequence as it is termed, were established using expert judgement by means of Failure Mode and Effects Analysis (FMEA). After the consequences were identified they were then grouped into 4 categories, these being personnel, equipment, environment and catch with each failure being rated from 1 to 4 linguistically. By combining the occurrence likelihood with the severity of the consequence a risk ranking was produced giving linguistically the risks associated with a failure of a certain component. This paper demonstrated the success that can be achieved using two different types of information and combining them to good effect.

A study of risk assessment of port security using fuzzy modelling (Ung (2007)) addressed the problem of deliberate or intentional damage from terrorism or criminal activity. Risk assessment deals with the likelihood and consequence of a possible event. A greater challenge was encountered as there was an unpredictable likelihood coupled with a high consequence. The study employs Failure Mode, Effects and Criticality Analysis (FMECA) but instead of using traditional historic data, fuzzy logic was used utilising linguistic terms as values. This was an obvious choice given the lack of data available. The sensitivity of the information made it unlikely to gather the required information. The study includes four elements, each with differing importance. The four elements introduced included: criticality of each asset, vulnerability of each asset, probability of occurrence and severity of occurrence. A greater importance was attached to criticality of each asset and vulnerability of each asset, with less importance given to probability of occurrence and severity of occurrence. This proved to be a useful aspect of this study as parameters with less importance may be considered without detracting from the important key parameters. Additionally, the expert judgement that was considered was given a differing weight to their opinions depending on their knowledge and experience. This methodology is useful given the often differing experience of experts used in research papers requiring expert judgement.

The inherent drawback of fuzzy modelling is the use of multiple parameters to describe multiple linguistic terms. This situation tends to generate a large number of fuzzy rules that need to be developed in order to model the system. A simple example of 5 parameters described using 5 linguistic terms requires 3,125 fuzzy rules. The advantages of using fuzzy logic systems previously outlined include a greater accuracy in decision making, a greater flexibility when applying it to differing problems and a reduction in human inconsistencies (Metaxiotis et al. (2003)).

4.3 Methodology of applying Fuzzy Logic

Applying delay-time analysis to a problem in order to establish an inspection interval using the environmental model E(T), using both objective information and subjective judgement, requires the development of a methodology. With a lack of data and the fact that some of the data required will be from an objective source, the methodology needs to address the combining of both types of data. The linguistic terms necessary to describe the parameters of both probability and costs must firstly be considered. This methodology will look firstly at a segment of the environmental model, namely the E_{health} term, in order to demonstrate the process. This term looks at the cost in terms of human injury. The terms $E_{collateral}$ and $E_{reverse}$ will then be examined, making up the remaining segments of the environmental model E(T). The modelling of this environmental model will demonstrate the use of linguistic terms to successfully model both conditional probability and consequence. The result will be a crisp value that can then be combined with the existing objective data in order to apply delay-time analysis environmental model.

A methodology of applying fuzzy logic to delay-time analysis is developed to include the following steps:

- Establish membership function.
- Develop a fuzzy rule base.
- Synthesize parameters.
- Defuzzify results.

4.3.1 Establish membership function

The membership functions for this methodology will deal with the conditional probability of occurrence and the costs associated with failure depending on the severity of the failure (consequence). The linguistic terms describing the linguistic variables will come from the use of expert judgement. Each expert is required to evaluate a proposition, 'x belongs to A'. A is a fuzzy set on a relevant universe X, representing a linguistic term with a given linguistic variable x, with $a_i(x)$ being a value of scores within a certain range of X. Furthermore, if there are n experts with equal knowledge and experience, then Equation (4.7) can be applied (Klir and Yuan (1995)):

$$A(x) = \frac{\sum_{i=1}^{n} a_i(x)}{n} \tag{4.7}$$

where, $A(x)$ is the final answer after the judgements made by the n experts have been combined and $a_i(x)$ is the answer given by an individual expert, $i \in n$.

If the experts have differing knowledge and experience then Equation (4.7) can be modified to reflect this, as illustrated in Equation (4.8):

$$A(x) = \sum_{i=1}^{n} Comp_i a_i(x) \tag{4.8}$$

where, $Comp_i$ is the degree of competency of the expert, and

$$\sum_{i=1}^{n} Comp_i = 1 \tag{4.9}$$

For this methodology the triangular membership function will be used as it gives a smooth transition from one linguistic state to another. The triangular membership also simplifies the defuzzification of each linguistic term (Ung (2005)).

The linguistic terms used to describe the conditional probability will be explored initially. The first step when establishing the conditional probability (CP) for a failure event would generally require the use of fault tree analysis (FTA) (Pillay and Wang (2003)). Fault tree analysis is a diagrammatic method that can establish the occurrence probability of an undesired top event, given a certain sequence or combination of failure events. This method though relies on historical data. The use of linguistic terms to describe the differing stages of probability is generated from expert judgement. The linguistic terms used for conditional probability (CP*n*) for this study are as follows:

- Remote (CP1).
- Low (CP2).
- Moderate (CP3).
- High (CP4).
- Very high (CP5).

A graphical representation of the membership function for conditional probability is illustrated in figure 4.2.

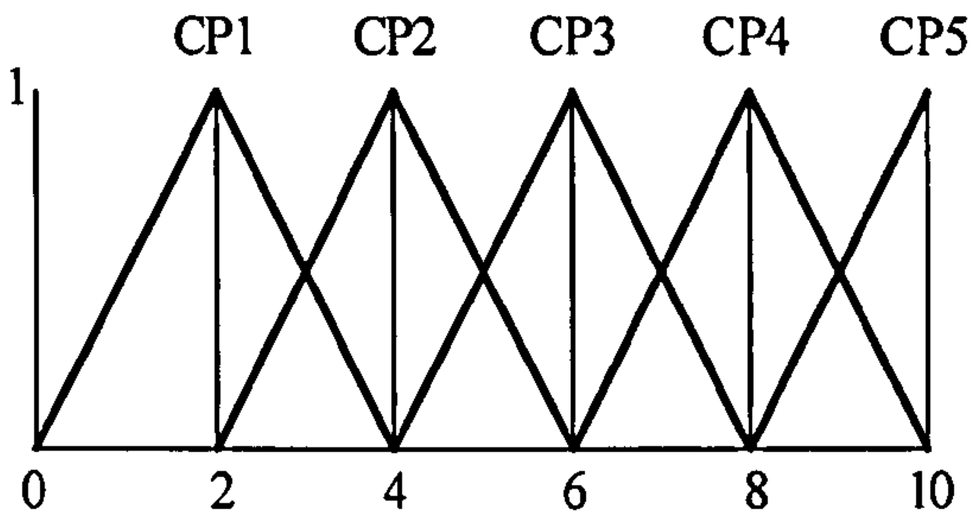


Figure 4.2. A membership function for conditional probability.

The linguistic terms used to describe the consequence will be based on cost. It should be noted however, the consequence is taking into account the costs associated with the severity of failure. The term E_{health} will look at the cost of human injury. This human injury can range from cuts and bruises to loss of life, possible guidelines for costs associated with personal injury and loss of life are available from the National Safety Council (NSC). The cost of *'loss of life'* is in the region of £1.8m, *'incapacitating injury'* £100k and *'non-incapacitating injury'* £12,000 (NSC (2008)). These costs can give a guide to possible consequences associated with E_{health} costs. $E_{collateral}$ will cover the costs associated with a failure leading to damage of plant items and buildings as well as residential buildings. The term E_{damage} will look at the cost of a failure requiring a clean-up process. The linguistic terms used for describing these consequences are:

- Negligible (C1).
- Marginal (C2).
- Moderate (C3).
- Critical (C4).
- Catastrophic (C5).

A graphical representation of the membership function for consequence is illustrated in figure 4.3.

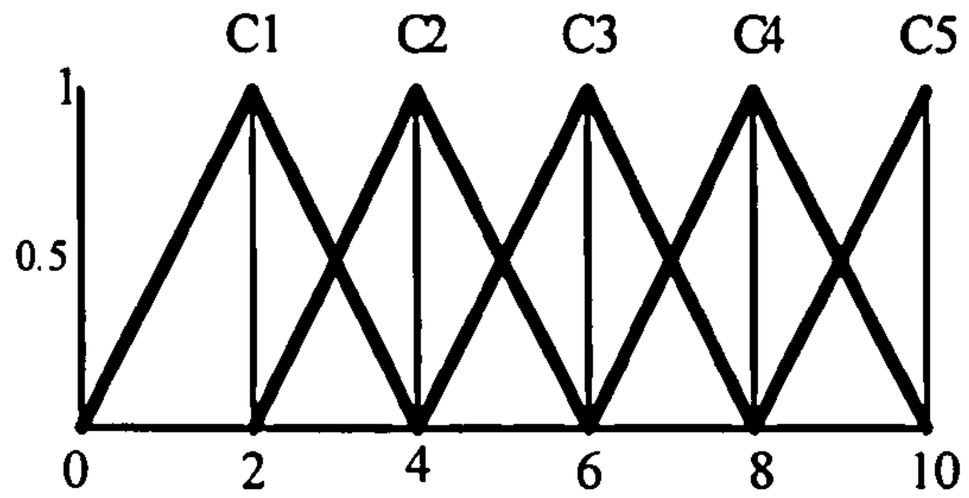


Figure 4.3. A membership function for consequence.

Once the linguistic terms describing the required parameters have been established, the task of developing a fuzzy rule base can take place.

4.3.2 Develop a fuzzy rule base

A fuzzy rule base is a system that is constructed using expert judgement in the form of IF / THEN rules (Wang (1997)). An IF / THEN rule begins with an input variable. The input of the fuzzy rule base in this case is the consequence of a failure and the probability of a failure. The output is the assigned linguistic variable, in this case environmental consequence (EC), assigned again using expert judgement. The fuzzy rule base developed, given a conditional probability and a consequence of a failure, assigns an environmental criticality (EC*n*). An example of this is: IF Consequence *C1* is *Negligible* and Probability *CP1* is *Remote* THEN Environmental Consequence (EC1) is established giving the result *Inexpensive*. In order to generate the fuzzy rule base, the experts are asked to group the various combinations into 5 groups, each reflecting a differing cost or expense ranging from EC1 to EC5. The term environmental criticality (EC*n*) is a measure of the risk, a combination of conditional probability and consequence, ranging from EC1 *inexpensive* to EC5 *disastrous*. The linguistic terms used for describing environmental consequence (EC) are:

- EC1 *Inexpensive.*
- EC2 *Reasonably expensive.*
- EC3 *Expensive.*
- EC4 *Very expensive.*
- EC5 *Disastrous.*

The membership function for the rules in the fuzzy rule base can be determined using Equation (4.7). The linguistic terms are subjective as the costs will differ from industry to industry. For example; a number of experts from a small manufacturing company might perceive inexpensive as below £500, whereby experts from an oil company might perceive inexpensive as below £10,000. For each category a rank is given relating to its importance, with each probability rank being added to each consequence rank. Using expert judgement, a compromise is found for each environmental consequence (EC*n*) based on the combination of the probability and the consequence. In addition to establishing an environmental consequence, ranging from EC1 to EC5, a belief structure is also required in order to give a greater accuracy to each rule. For instance, looking at rule 3 and rule 4, they both share the outcome of EC2, reasonably expensive, but rule 3 has a consequence of C3 (moderate) while rule 4 has a consequence of C4 (critical). A belief structure will be able to differentiate between the two EC2 results with rule 3 having a belief structure of (1) for EC2 and rule 4 having a belief structure of (0.80) for EC2 and (0.20) for EC3. A fuzzy rule base using the inputs *consequence* C*n* and *probability* CP*n* has been developed, together with a belief structure (*n*), resulting in the following 25 rules:

Rule 1: If consequence C1 and probability CP1 then EC1 (1)

Rule 2: If consequence C2 and probability CP1 then EC1 (0.80; EC2 0.20)

Rule 3: If consequence C3 and probability CP1 then EC2 (1)

Rule 4: If consequence C4 and probability CP1 then EC2 (0.80; EC3 0.20)

Rule 5: If consequence C5 and probability CP1 then EC3 (1)

Rule 6: If consequence C1 and probability CP2 then EC1 (0.80; EC2 0.20)

Rule 7: If consequence C2 and probability CP2 then EC2 (1)

Rule 8: If consequence C3 and probability CP2 then EC2 (0.80; EC3 0.20)

Rule 9: If consequence C4 and probability CP2 then EC3 (1)

Rule 10: If consequence C5 and probability CP2 then EC3 (0.80; EC4 0.20)

Rule 11: If consequence C1 and probability CP3 then EC2 (1)

Rule 12: If consequence C2 and probability CP3 then EC2 (0.80; EC3 0.20)

Rule 13: If consequence C3 and probability CP3 then EC3 (1)

Rule 14: If consequence C4 and probability CP3 then EC3 (0.80; EC4 0.20)

Rule 15: If consequence C5 and probability CP3 then EC4 (1)

Rule 16: If consequence C1 and probability CP4 then EC2 (0.80; EC3 0.20)

Rule 17: If consequence C2 and probability CP4 then EC3 (1)

Rule 18: If consequence C3 and probability CP4 then EC3 (0.80; EC4 0.20)

Rule 19: If consequence C4 and probability CP4 then EC4 (1)

Rule 20: If consequence C5 and probability CP4 then EC5 (1)

Rule 21: If consequence C1 and probability CP5 then EC3 (1)

Rule 22: If consequence C2 and probability CP5 then EC3 (0.80; EC4 0.20)

Rule 23: If consequence C3 and probability CP5 then EC4 (1)

Rule 24: If consequence C4 and probability CP5 then EC5 (1)

Rule 25: If consequence C5 and probability CP5 then EC5 (1)

It is important to point out that rules 20, 24 and 25 have a difference in consequence or probability but display the same outcome and belief structure (i.e. EC5 with a belief degree of 1). This is because both consequences, critical and catastrophic, have serious implications when given a probability of either high or very high.

4.3.3 Synthesise parameters

Given the opinion of an expert, a synthesis of both consequence and probability can now take place. To illustrate this, an expert (i.e. expert #1) is

asked to give an opinion of each cost for E_{health} ranging from CL_1 to CL_5. To give an example, looking firstly at CL_1, the expert believes that CL_1 would be 5 on a scale of 1 to 10, giving a belief of 0.5 for C2 and 0.5 for C3. Similarly, the expert will give an opinion for a probability of each consequence of E_{health} ranging from P_1 to P_5 for each conditional probability (CP*n*). Here the expert believes that CL_1 would have a conditional probability of 4.5 on a scale of 1 to 10, giving a belief of 0.75 for CP2 and 0.25 for CP3. This example is demonstrated below together with a graphical representation of the membership functions for both cost and probability, illustrated in figure 4.4 and figure 4.5 respectively.

Expert #1

CL_1 *(C1 = 0) (C2 = 0.5) (C3 = 0.5) (C4 = 0) (C5 = 0)*

P_1 *(CP1 = 0) (CP2 = 0.75) (CP3 = 0.25) (CP4 = 0) (CP5 = 0)*

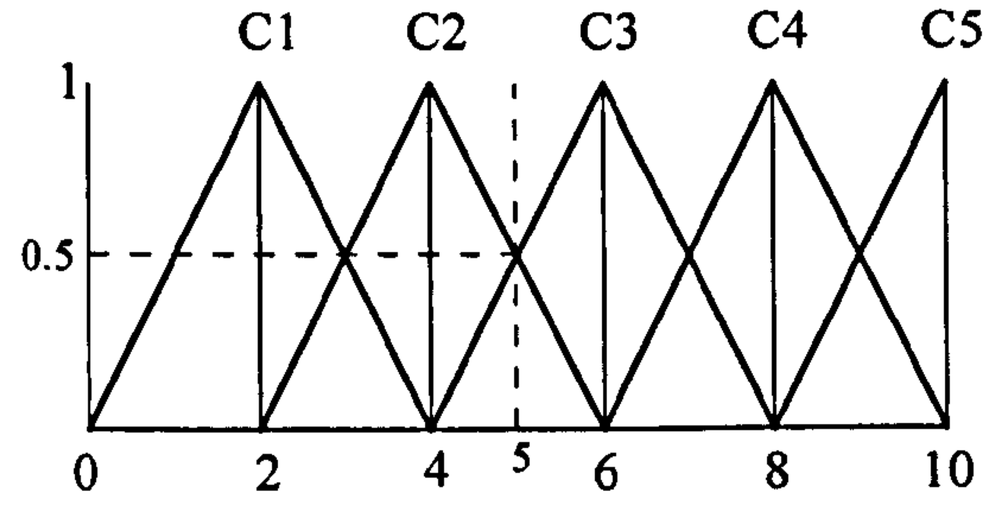


Figure 4.4. The membership function for CL_1.

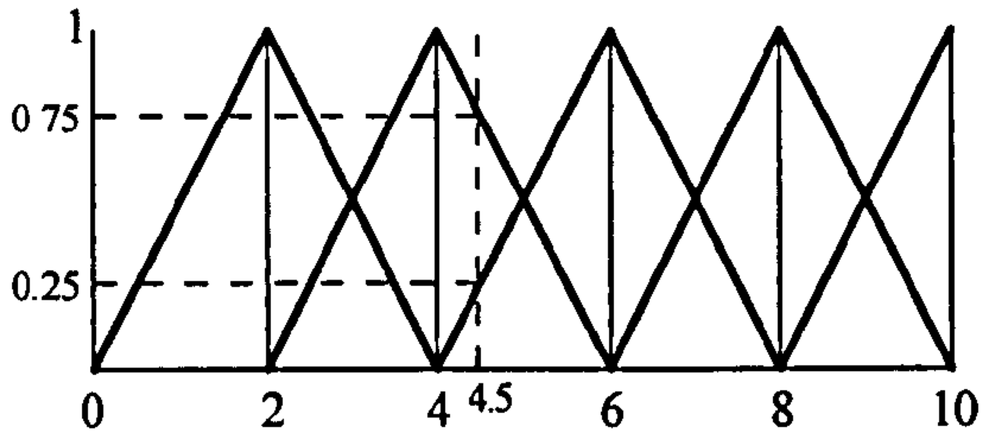


Figure 4.5. The membership function for probability P_1

Each value of CL_n is combined with each value of probability (P_n). An important point to note is if a zero (0) is given to a linguistic term, for example, C1 and CP1, the result is 'no score' for the combination. This synthesis will use 'max-min' inference to establish the environmental criticality (EC). The first step is to take the 'minimum' value for CL_1 and probability P_1. Referring to the fuzzy rule-base developed in section 4.3.2, the results for this example are shown to be:

C2 (0.5) and CP2 (0.75)	*EC2 0.5*	*Rule 7 fired*
C2 (0.5) and CP3 (0.25)	*EC2 0.25, EC3 0.20*	*Rule 12 fired*
C3 (0.5) and CP2 (0.75)	*EC2 0.5, EC3 0.20*	*Rule 8 fired*
C3 (0.5) and CP3 (0.25)	*EC3 0.25*	*Rule 13 fired*

Continuing with this example, the next step is to take the worst case scenario from the figures gathered, i.e. taking the maximum figure from each linguistic term. The result of modelling for *expert #1 (i.e. CL_1* and *P_1)* would therefore be:

Expert #1- CL_1 and *P_1= (EC2, 0.5);(EC3, 0.25)*

The environmental consequence for E_{health}, ranging from EC1 to EC5 can be defined in monetary terms using expert judgement. The costs associated with each environmental consequence term will not only be specific to the industry in question, but the plant facility or factory in question.

4.3.4 Defuzzify results

The defuzzification process creates a single crisp value based on the fuzzy conclusion, in this case expressing the environmental consequence of a particular event. This process can also give a prioritisation to several possible scenarios, thus ranking a scenario based on risk. For this particular study a normalisation of the

worst case scenario is considered given the impact of the environmentally damaging effects that could result from failure.

Having established an environmental criticality for CL_1 and probability P_1 (i.e. EC2 0.5, EC3 0.25), a normalisation of these figures can now take place. It serves to transform the data gathered into an overall sum of 1 making therefore each part of the data representative of the whole. To illustrate this, continuing with the above example, taking the membership of EC2, 0.5 and adding this to the membership of EC3, 0.25, would give a total of 0.75. The next step is to divide the first figure, in this case 0.5 with the total, 0.75 giving 0.67 and dividing the second figure, 0.25 with 0.75 giving 0.33. The normalisation of CL_1 and probability P_1 can now be put into a crisp value. For example, if EC2 is given a value of £10,000 and EC3 given a value of £25,000 then the following calculation can take place:

Expert #1- EC2 (0.67 x £10,000) + EC3 (0.33 x £25,000) = £14,950

The benefit of normalisation is not realised until there are more than two parameters to deal with. For example, if the above example was to have the addition of the value EC4 0.10, where EC4 is given a value of £50,000, then this could be taken into account without distorting the results.

EC2 (0.59 x £10,000) + EC3 (0.29 x £25,000) + EC4 (0.12 x £50,000) = £19,150

When using expert judgement for fuzzy applications, there should generally be a minimum of three experts used for an accurate analysis to take place. Ideally, five experts may be an optimum number to use as this reduces errors that may arise due to an ambiguous value (Christer (1998b)). For this example, two additional expert opinions are added to *expert #1* opinion, namely; *expert #2* and *expert #3*. Taking the additional experts' opinions and calculating the value of this result gives:

Expert #1	*(EC2, 0.67);(EC3, 0.33)*	*(£14,950)*
Expert #2	*(EC2, 0.58);(EC3, 0.42)*	*(£16,300)*
Expert #3	*(EC2, 0.75);(EC3, 0.25)*	*(£13,750)*

A unification of the three expert opinions using Equation (4.7) can now take place, adding each of the experts' opinions together and dividing by the number of experts used, in this case 3, giving:

$$(£14,950 + £16,300 + £13,750)/3 = £15,000$$

In this example, the cost of E_{health} would be £15,000. This process can be repeated for all of the parameters that make up the subjective terms for E(T), namely E_{impact} and E_{damage}.

4.4 Case study

In order to demonstrate the above methodology a case study of a factory producing carbon black in the UK is given. A detailed description of the factory can be found in section 3.4. A detailed description of the impact of failure of a filter bag on the environment as well as the costs relating to the failure of a filter bag both directly and indirectly can be found in section 3.4.2.

4.4.1 The application of applying fuzzy logic

In order to apply the environmental model E(T), there are a number of objective parameters required. This objective data that has been gathered has been taken from historical means, i.e. inspection reports, maintenance reports, etc. The data gathered as part of this case study is as follows:

- Arrival rate of a defect, k_f 0.28 per day.
- Mean time between failure (MTBF) 1095 days.
- Downtime due to inspection 0.1 days.
- Downtime for a breakdown repair 7 days.

The subjective parameters that are needed in order to complete the delay-time analysis environmental model E(T) are as follows:

- E_{health}
- $E_{collateral}$
- E_{damage}
- $E_{reverse}$

For this case study the term E_{health} will be examined firstly in greater detail in order to provide a demonstration of the methodology. There are three experts used for this case study each with equal knowledge and experience. The first expert is currently a section manager with 15 years experience in the process industry. He holds a HND in electrical, instrument and process control engineering as well as being a time served electrician. The second expert is currently a reliability engineer with 21 years experience in the process industry, his qualifications are to degree standard. The third expert is an engineering manager with 14 years experience in the engineering and process industry. His qualifications are also to degree standard. Each expert was given the task of identifying firstly, a conditional probability then secondly a consequence of failure of a filter bag. The information was given out in isolation of the other experts in order to ensure that each opinion was an individual opinion.

4.4.2 Establishing E_{health}

The membership functions of C1 to C5 were obtained using Equation (4.7) and the three experts' judgements. Expert #1 was asked to highlight consequence costs, CL_1 to CL_5 on this graph. Both the membership functions and the cost consequence CL_1 to CL_5 for expert #1 are illustrated in figure 4.6.

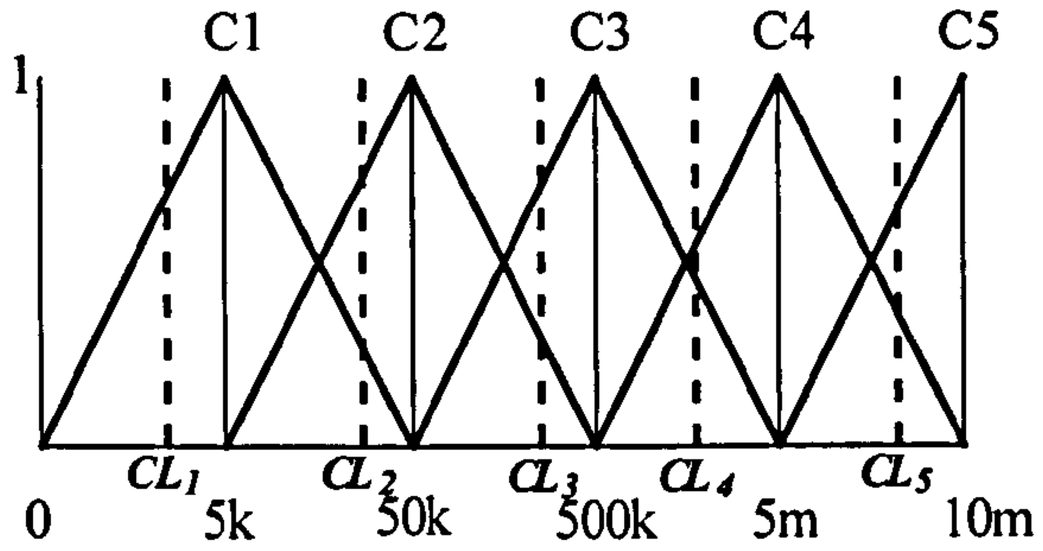


Figure 4.6. Membership function of consequence of E_{health} from expert #1.

The details of the results from this membership function are as follows:

CL_1 *(C1 = 0.67) (C2 = 0) (C3 = 0) (C4 = 0) (C5 = 0)*

CL_2 *(C1 = 0.28) (C2 = 0.72) (C3 = 0) (C4 = 0) (C5 = 0)*

CL_3 *(C1 = 0) (C2 = 0.28) (C3 = 0.72) (C4 = 0) (C5 = 0)*

CL_4 *(C1 = 0) (C2 = 0) (C3 = 0.44) (C4 = 0.56) (C5 = 0)*

CL_5 *(C1 = 0) (C2 = 0) (C3 = 0) (C4 = 0.36) (C5 = 0.64)*

A graphical representation of probability was also constructed taken from the opinion of expert #1. The probability ranged from P_1 to P_5, where P_1 is the conditional probability of CL_1, P_2 is the conditional probability of CL_2, and P_3 is the conditional probability of CL_3 illustrated in figure 4.7. It is worth highlighting that none of the experts' believed that there is a probability of CL_4 (cost of disability) or CL_5 (cost of loss of life) given failure of a filter bag.

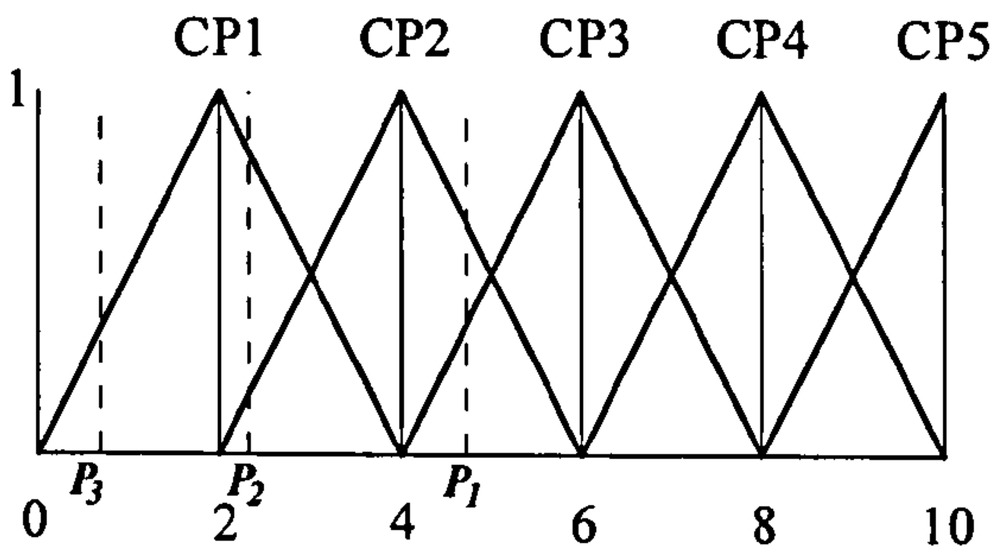


Figure 4.7. Membership function of conditional probability of E_{health} from expert #1.

The details of the differing probabilities are as follows:

P_1 *(CP1 = 0) (CP2 = 0.62) (CP3 = 0.38) (CP4 = 0) (CP5 = 0)*

P_2 *(CP1 = 0.84) (CP2 = 0.16) (CP3 = 0) (CP4 = 0) (CP5 = 0)*

P_3 *(CP1 = 0.35) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)*

P_4 *(CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)*

P_5 *(CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)*

Combining each consequence with each probability and assigning an environmental consequence (EC*n*) referring to the rules generated in section 4.3.2 can now take place. Each expert was asked to consider the failure of a filter bag and to assign a cost consequence, CL_n and a conditional probability P_n accordingly.

CL_1; probability P_1

C1 (0.67) and CP2 (0.62)	*EC1 0.62, EC2 0.20*	*Rule 6 fired*
C1 (0.67) and CP3 (0.38)	*EC2 0.38*	*Rule 11 fired*

CL_2; probability P_2

C1 (0.28) and CP1 (0.84)	*EC1 0.28*	*Rule 1 fired*
C1 (0.28) and CP2 (0.16)	*EC1 0.16, EC2 0.16*	*Rule 6 fired*
C2 (0.72) and CP1 (0.84)	*EC1 0.72, EC2 0.20*	*Rule 2 fired*
C2 (0.72) and CP2 (0.16)	*EC2 0.16*	*Rule 7 fired*

CL_3; probability P_3

C2 (0.28) and CP1 (0.35)	*EC1 0.28, EC2 0.20*	*Rule 2 fired*
C3 (0.72) and CP1 (0.35)	*EC2 0.35*	*Rule 3 fired*

Having carried out the process of comparing the cost (CL_n) with the probability (P_n), a model result can now be extracted from these figures from expert #1. This part of the process will take the maximum from each cost - probability score comparison.

Expert #1 results

CL_1; probability P_1	*EC1 0.62; EC2 0.38*
CL_2; probability P_2	*EC1 0.72; EC2 0.20*
CL_3; probability P_3	*EC1 0.28; EC2 0.35*

The next step is to normalise this result giving:

CL_1; probability P_1	*EC1 0.62; EC2 0.38*
CL_2; probability P_2	*EC1 0.78; EC2 0.22*
CL_3; probability P_3	*EC1 0.44; EC2 0.56*

The same process was repeated for expert #2 and expert #3, the results of which are illustrated below.

Expert #2 results

CL_1; probability P_2 *EC1 0.44; EC2 0.56*

CL_2; probability P_1 *EC1 0.59; EC2 0.41*

CL_3; probability P_3 *EC1 0.46; EC2 0.39*

Normalising:

CL_1; probability P_2 *EC1 0.44; EC2 0.56*

CL_2; probability P_1 *EC1 0.59; EC2 0.41*

CL_3; probability P_3 *EC1 0.54; EC2 0.46*

Expert #3 results

CL_1; probability P_3 *EC1 0.42; EC2 0.41*

CL_2; probability P_2 *EC1 0.55; EC2 0.33*

CL_3; probability P_3 *EC1 0.32; EC2 0.27*

Normalising:

CL_1; probability P_3 *EC1 0.51; EC2 0.49*

CL_2; probability P_2 *EC1 0.63; EC2 0.37*

CL_3; probability P_3 *EC1 0.54; EC2 0.46*

Having established a cost consequence (CL_n) and conditional probability (P_n), resulting in an environmental criticality with a belief value for the failure of a filter bag, a monetary value is required for each environmental consequence EC*n*. The EC*n* figure can differ from industry to industry, but when dealing with the term E_{health}, loss of life and injury will have similar cost associated with it regardless of the industry considered. A guideline for establishing costs relating to E_{health} (NSC (2008)) was considered together with the experts' opinion has

established figures for each environmental consequence:

EC1 = £10k

EC2 = £50k

EC3 = £250k

EC4 = £1m

EC5 = £5m

Defuzzification of the experts' opinion can now take place. By assigning a cost to each environmental criticality (EC*n*) and applying these costs to each normalised judgement for cost CL_n and probability P_n, a single crisp value can now be gathered, as illustrated:

Expert #1 results

CL_1; probability P_1 *(£10,000 ×0.62) + (£50,000 ×0.38) = £25,200*

CL_2; probability P_2 *(£10,000 ×0.78) + (£50,000 ×0.22) = £18,800*

CL_3; probability P_3 *(£10,000 ×0.44) + (£50,000 ×0.56) = £32,400*

Expert #2 results

CL_1; probability P_1 *(£10,000 ×0.44) + (£50,000 ×0.56) = £32,400*

CL_2; probability P_2 *(£10,000 ×0.59) + (£50,000 ×0.41) = £26,400*

CL_3; probability P_3 *(£10,000 ×0.54) + (£50,000 ×0.46) = £28,400*

Expert #3 results

CL_1; probability P_1 *(£10,000 ×0.51) + (£50,000 ×0.49) = £29,600*

CL_2; probability P_2 *(£10,000 ×0.63) + (£50,000 ×0.37) = £24,800*

CL_3; probability P_3 *(£10,000 ×0.54) + (£50,000 ×0.56) = £33,400*

From the crisp figures gathered from the three experts unification can now take place, using Equation (4.7), in order to establish a single figure for E_{health}.

CL_1: £25,200 + £32,400 + £29,600 / 3 = £29,067

CL_2: £18,800 + £26,400 + £24,800 / 3 = £23,333

CL_3: £32,400 + £28,400 + £33,400 / 3 = £31,400

This gives the term E_{health} a total value of £83,800. The remaining costs which make up the term E_{health} (costs CL_4 and CL_5) have been deemed unnecessary by the experts and therefore disregarded for failure of a filter bag.

The next task is to establish costs relating to collateral damage and clean-up due to failure.

4.4.3 Establishing $E_{collateral}$

As discussed earlier in this chapter, $E_{collateral}$ attempts to deal with the risk of damage to plant items and buildings plus damage to residential buildings due to failure. This study will continue to look at failure of a filter bag and its effects on collateral damage to plant and buildings. Again, the three experts were asked to estimate the cost to plant buildings and to residential building. The same scale has been used here as was used for E_{health} relating to cost, i.e. C1 to C5. Looking at the opinion of expert #1, the term $cost_{plant}$ has a membership of 0.28 of C3 and 0.72 of C4, as illustrated in figure 4.7. Subsequently, expert #1 was asked to give a cost relating to the term $cost_{res}$ dealing with residential damage, again this is illustrated in figure 4.8. This term has been given a membership of 0.60 of C2 and 0.40 of C3.

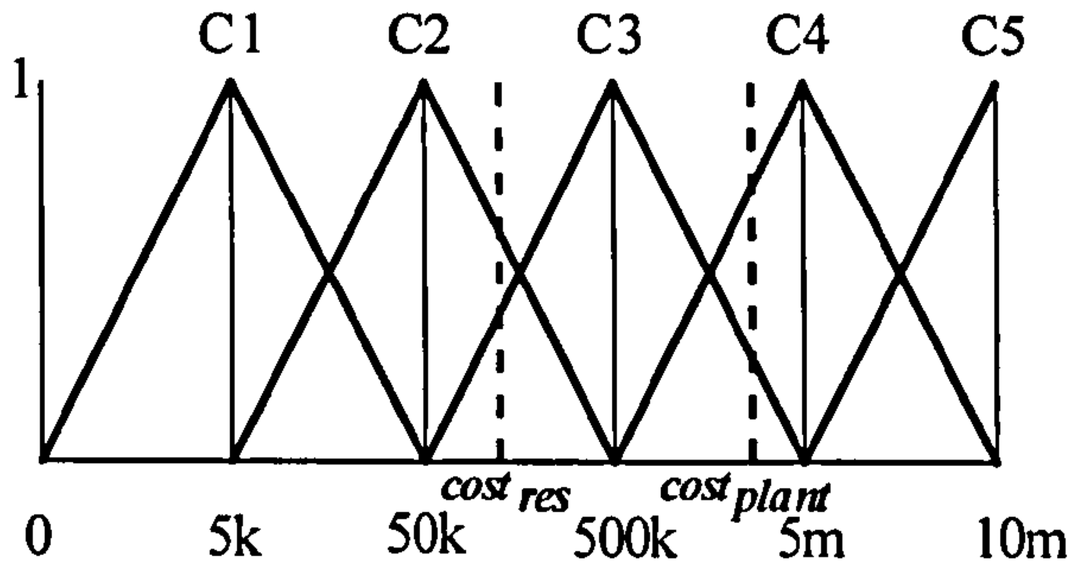


Figure 4.8. Membership function of consequence of $E_{collateral}$ from expert #1.

Having established costs relating to plant damage and residential damage a probability is now required for each term. The scale used for the term E_{health} has been used. Expert #1 assigned a probability of P_{plant} for $cost_{plant}$ giving a membership of 0.84 for CP1 and 0.16 for CP2, with probability P_{res} having a membership of 0.35 for CP1 as illustrated in figure 4.9.

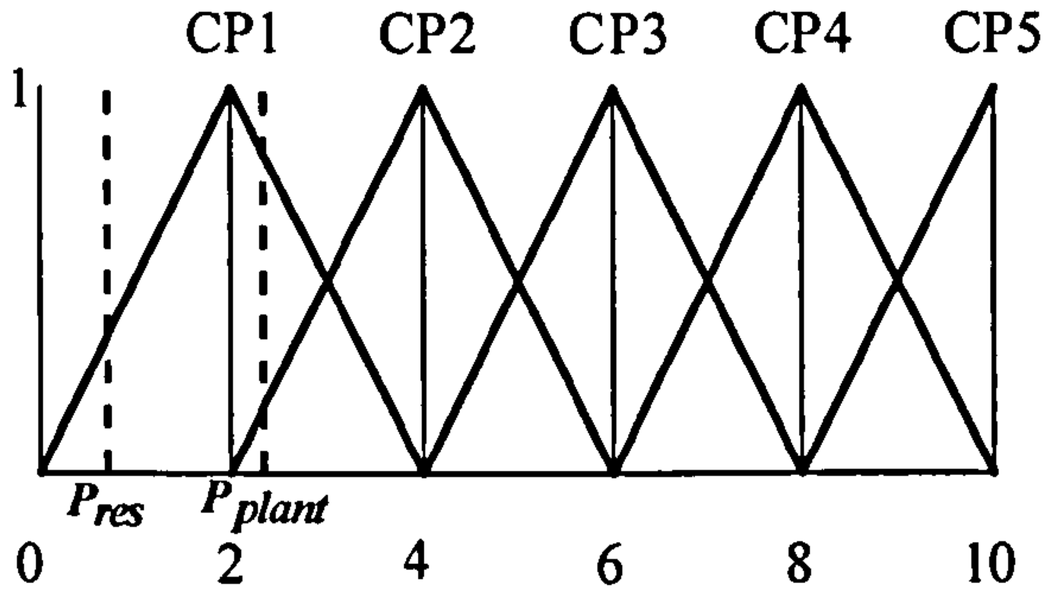


Figure 4.9. Membership function of conditional probability of $E_{collateral}$ from expert #1.

Again, as with the term E_{health}, each consequence with each probability can be assigned an environmental consequence (EC*n*) referring to the rules generated in section 4.3.2.

Expert #1 results:

$Cost_{plant}$; probability P_{plant}

C3 (0.28) and CP1 (0.84)	*EC2 0.28*	*Rule 3 fired*
C3 (0.28) and CP2 (0.16)	*EC2 0.16, EC3 0.16*	*Rule 8 fired*
C4 (0.72) and CP1 (0.84)	*EC2 0.72, EC3 0.20*	*Rule 4 fired*
C4 (0.72) and CP2 (0.16)	*EC3 0.16*	*Rule 9 fired*

$Cost_{res}$; probability P_{res}

C2 (0.60) and CP1 (0.35)	*EC1 0.35, EC2 0.20*	*Rule 2 fired*
C3 (0.40) and CP1 (0.35)	*EC2 0.35*	*Rule 3 fired*

The above results can now be synthesised as:

$Cost_{plant}$; probability P_{plant}	*EC2 0.72; EC3 0.20*
$Cost_{res}$; probability P_{res}	*EC1 0.35; EC2 0.35*

The next step is to normalise this result giving:

$Cost_{plant}$; probability P_{plant}	*EC2 0.78; EC3 0.22*
$Cost_{res}$; probability P_{res}	*EC1 0.50; EC2 0.50*

Defuzzification of expert #1's opinion can now take place, assigning a cost to each environmental criticality (EC*n*) and applying these costs to each normalised judgement for cost and probability. A single crisp value for $E_{collateral}$ can now be established relating to the term for collateral damage. The costs previously assigned to each environmental criticality, EC*n*, have been used for collateral damage.

Expert #1 results:

$Cost_{plant}$; probability P_{plant} $\quad (£50,000 \times 0.78) + (£250,000 \times 0.22) = £94,000$

$Cost_{res}$; probability P_{res} $\quad (£10,000 \times 0.50) + (£50,000 \times 0.50) = £30,000$

From this result it is shown that the opinion of expert #1 for the risks associated to the cost of collateral damage is £124,000. This process was repeated for experts #2 and #3 (see appendix 2). The results of the three experts' opinion were then considered, using Equation (4.7), to give a single crisp value:

$E_{collateral}$ cost £124,000 + £145,600 + 130,000 / 3 = £133,000

4.4.4 Establishing E_{damage}

As described earlier in this chapter, the term E_{damage} relates to the impact of a failure on the environment, i.e. spillage or leakage, which requires clean-up. The term $cost_{clean}$ as well as a probability are the parameters for this term in order to establish a risk in terms of cost. The cost of environmental damage can differ greatly depending on the industry in question. As with the health parameter and the collateral parameter three expert opinions were gathered to establish a cost relating to environmental damage. Similarly from the other parameters established, expert #1 opinion was that of $cost_{clean}$ having a membership of 0.20 for c3 and 0.80 for c4 illustrated graphically in figure 4.10.

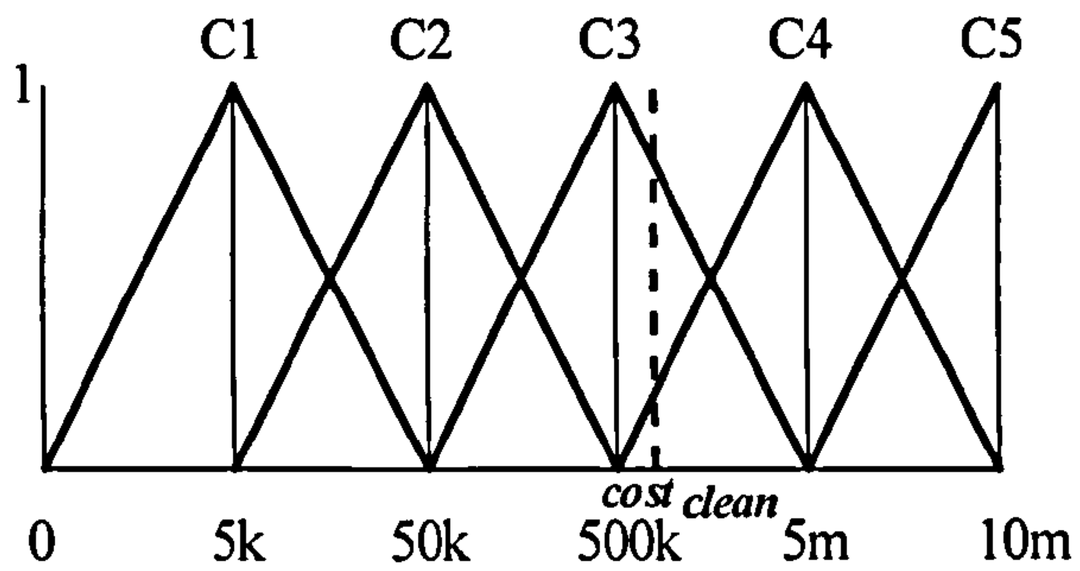


Figure 4.10. Membership function of consequence of E_{damage} from expert #1.

Having established costs relating to environmental clean-up a probability is now required for the term. Again, the scale for the term E_{health} has been used, assigning a probability of P_{clean} illustrated in figure 4.11.

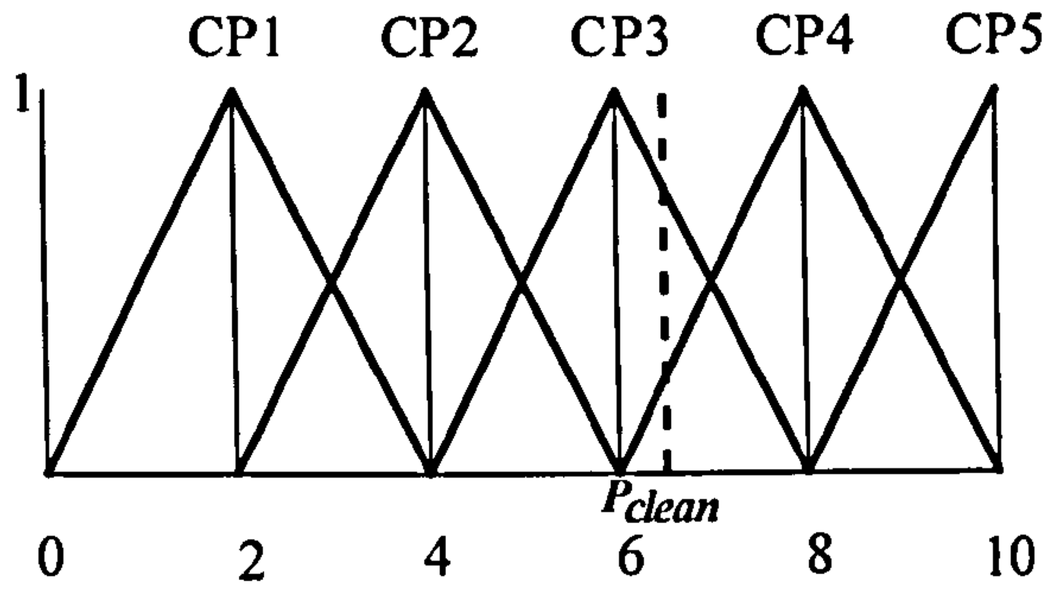


Figure 4.11. Membership function of conditional probability of E_{damage} from expert #1.

Expert #1 assigned a membership of 0.74 for CP3 and 0.26 for CP4. Given this information an environmental consequence (EC*n*) can be established.

Expert #1 results:

$Cost_{clean}$; probability P_{clean}

C3 (0.20) and CP3 (0.74)	*EC3 0.20*	*Rule 13 fired*
C3 (0.20) and CP4 (0.26)	*EC3 0.20, EC4 0.20*	*Rule 18 fired*
C4 (0.80) and CP3 (0.74)	*EC3 0.74, EC4 0.20*	*Rule 14 fired*
C4 (0.80) and CP4 (0.26)	*EC4 0.26*	*Rule 19 fired*

Expert #1 results:

$Cost_{clean}$; probability P_{clean}	*EC3 0.74; EC4 0.26*

Normalising this result gives:

$Cost_{clean}$; probability P_{clean}	*EC3 0.74; EC4 0.26*

Defuzzification of expert #1's opinion can now take place, assigning a cost to each environmental criticality (EC*n*) as previously demonstrated, and applying these costs to each normalised judgement for cost and probability. A single crisp value for E_{damage} can now be established relating to the term for environmental damage.

Expert #1 results:

$Cost_{clean}$; probability P_{clean}	*(£250,000 × 0.74) + (£1m × 0.26) = £445,000*

From this result it is shown that the opinion of expert #1 for the risks associated to the cost of environmental damage is £445,000. This process was repeated for experts #2 and #3 (see appendix 2). The results of the three experts' opinion were then considered, using Equation (4.7), to give a single crisp value of £445,000.

Having established a cost for the term E_{damage} it is a straightforward task to establish a cost for $E_{reverse}$. With reference to Equation (4.7) it can be seen that a factor needs to be selected from Table 4.1. With this case study looking at the product of carbon black it is the opinion of the experts that a factor of 0.2 is realistic. Given this information a figure of £556,250 is calculated for the term $E_{reverse}$.

Applying the results gathered from the three experts to the environmental model E(T), Equation (4.1), can now take place. The objective data (section 4.4.1) has been gathered from historical means, i.e. inspection and maintenance reports. This will make up part of the environmental model E(T). The remaining parameters have come from expert judgement, the environmental costs established being:

E_{health}: £83,800
$E_{collateral}$: £133,000
E_{damage}: £445,000
$E_{reverse}$: £556,250

When the objective data together with the subjective data is applied to the environmental model E(T) an inspection period, based on minimising the environmental impact of a failure, can be achieved. The outcome is illustrated graphically, as shown in figure 4.12.

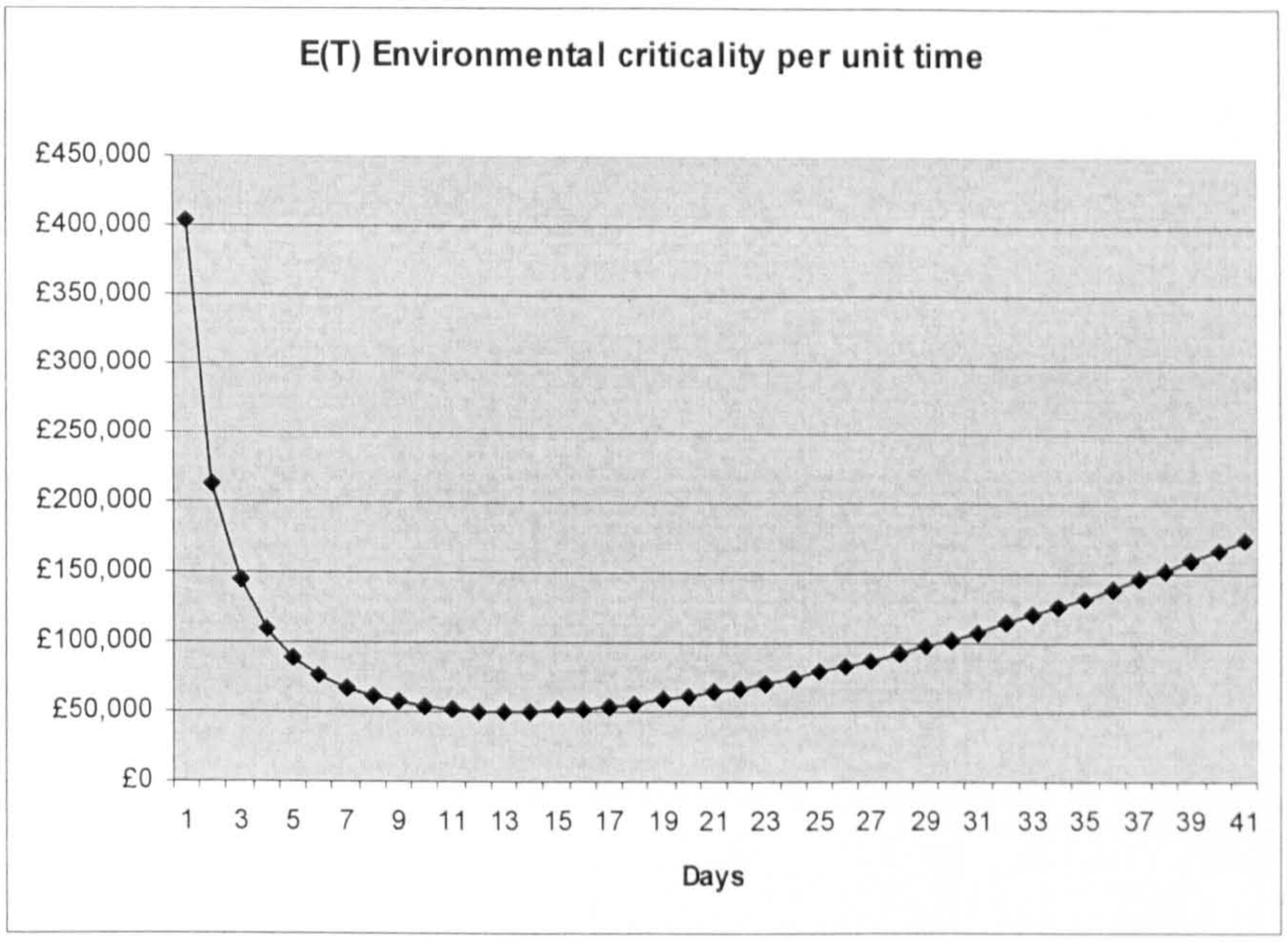


Figure 4.12. Optimal inspection interval based on minimal cost.

Figure 4.12 shows graphically the environmental impact cost of an inspection interval ranging from 1 day to 41 days. The graph illustrates a minimum inspection interval of 13 days with a cost of £50,406.

4.4.5 Validation

In order to validate the environmental model E(T) a sensitivity analysis was carried out to consider the effect of change to the results. The analysis varied the input data, E_{impact} and E_{damage}, increasing and decreasing each by 5% and 10%. This resulted in no change to the inspection interval but had obvious changes to the environmental impact costs.

An increase of 10% in the costs relating to the terms E_{impact} and E_{damage} resulted in an increase of £5,041 to give a total of £55,447. Similarly both E_{impact} and E_{damage} were increased by 5% resulting in an increase of £2,521 giving a total

of £52,927. Decreasing E_{impact} and E_{damage} by 10% gave a reduction of £5,040 resulting in a cost of £45,366. A reduction of 5% resulted in a decrease of £2,520 giving a total of £47,886. These figures are illustrated in table 4.1.

Table 4.1. Sensitivity analysis of increasing and decreasing E_{impact} and E_{damage}

% Change	Environmental cost	Inspection interval
10%	£55,447	13 days
5%	£52,927	13 days
Unchanged	£50,406	13 days
-5%	£47,886	13 days
-10%	£45,366	13 days

The validation can also be illustrated graphically as shown in figure 4.13.

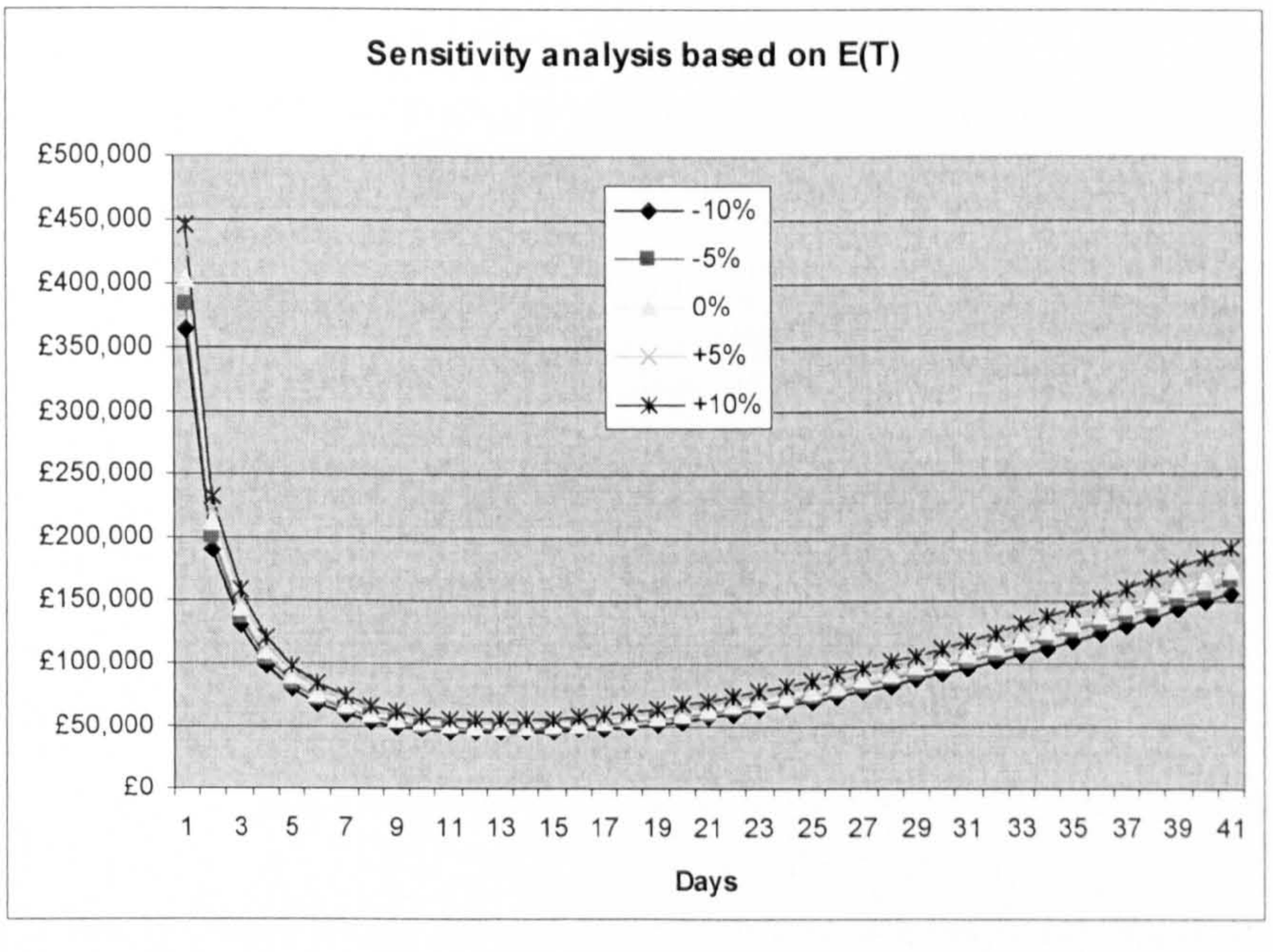


Figure 4.13. Optimal inspection period based on minimal cost to the environment.

4.4.6 Compare results with previous study

Chapter 3 established the environmental model E(T) using expert judgement. The experts were asked to give a figure for each of the parameters relating to the consequential costs associated with the failure of a filter bag. They were also asked to give an estimation of the probability of each parameter leading to the particular outcome of each parameter. The results of this exercise are illustrated in table 3.2, section 3.4.3 of chapter 3. The aim of this chapter is to reproduce the environmental model using fuzzy logic generated data. In order to perform a direct comparison, all of the parameters relating to the downtime model D(T) and cost model C(T) have remained unchanged, the data relating to the parameters of the environmental model E(T) have been replaced with data established using fuzzy logic. The comparison between the original data to establish the environmental model E(T) and the data established using fuzzy logic is illustrated in table 4.2.

Table 4.2. A comparison between the original environmental modelling data and the fuzzy logic generated environmental modelling data.

	Original data	Fuzzy logic data
E_{health}	£5,000	£83,800
$E_{collateral}$	£375,000	£133,000
E_{damage}	£200,000	£445,000
$E_{reverse}$	£250,000	£556,250
E_{impact}	£630,000	£773,050

Table 4.2 clearly illustrates a significant difference between the original data and that of the fuzzy logic generated data. The fuzzy logic data relating to the environmental model has been integrated into the delay-time analysis model alongside the original environmental modelling data from chapter 3, illustrated in

figure 4.14. The outcome of the fuzzy logic inclusion is to establish an improved inspection interval.

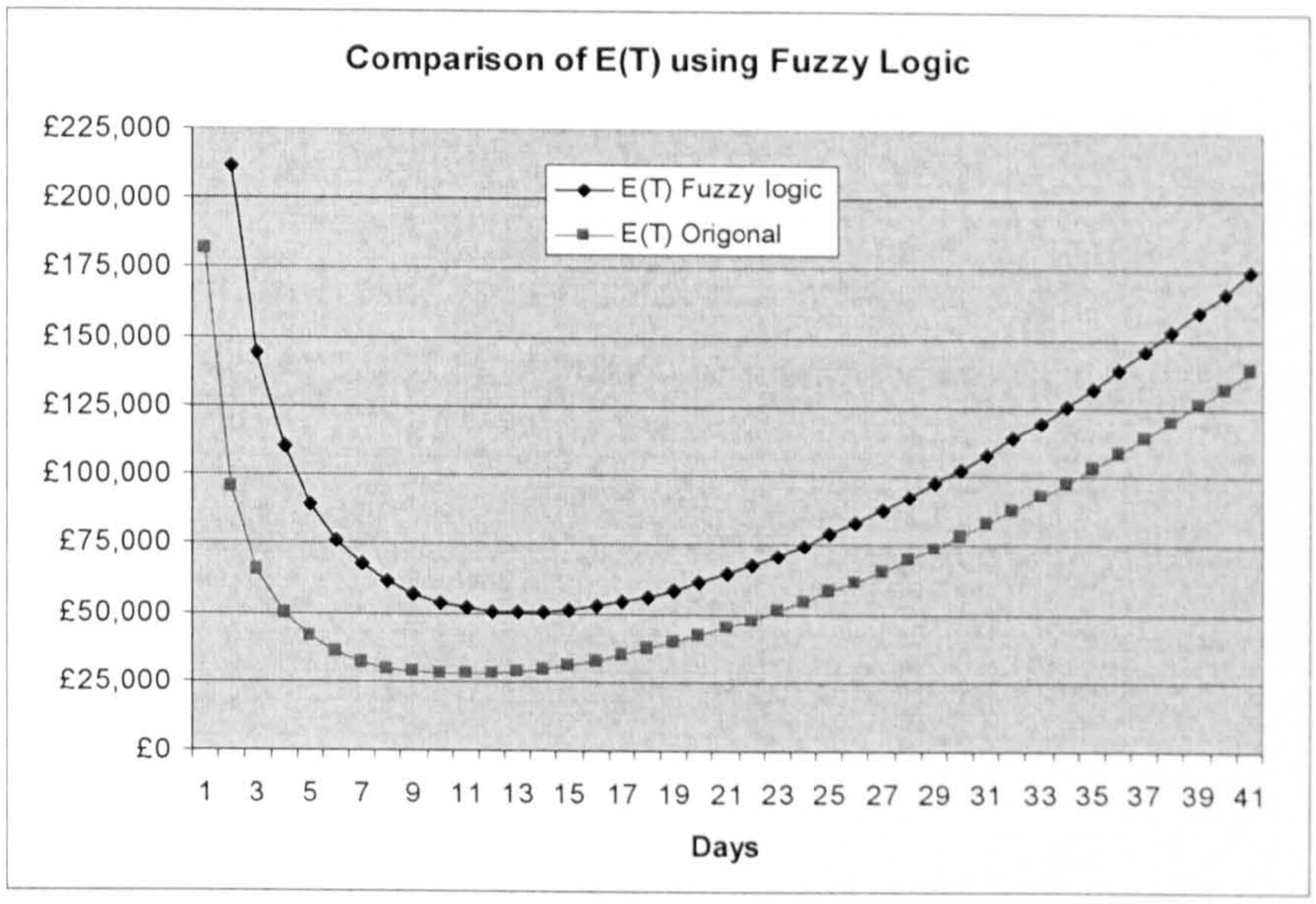


Figure 4.14. Comparison of E(T) using fuzzy logic developed data.

When the fuzzy logic generated data is added to the delay-time analysis model, the environmental model E(T) also shows a significant change. As illustrated in figure 4.14, the inspection interval has moved from 11 days to that of 13 days but more noticeably the environmental costs relating to failure has increased from £27,624 to £50,406 which is almost twice the original estimate. The difference in the results in this chapter compared to the results in chapter 3 is due to the estimation of the environmental modelling parameters in chapter 3 whereby general approximation values were given. The modelling of costs in this chapter has been conducted in a detailed and meticulous manner with each expert judgement synthesised in a rational way.

4.5 Discussion

The aim of this case study has been to apply delay-time analysis, a maintenance modelling technique, to a company producing carbon black. The challenge was to use both subjective expert judgement together with objective historical data. The reason for combining the differing types of data comes from the information required to applying the environmental model of the delay-time analysis method (Jones et al. (2009)). This environmental model looks at the consequence of failure of a component on the environment. This methodology relies heavily on expert judgement to quantify parameters such as loss of life, injury, collateral damage and clean-up costs into an overall cost risk, resulting in an inspection interval based on these factors.

Current practice at the company is that of once weekly inspections, this study can suggest that the inspection interval could move to a once fortnightly inspection regime. However, given the facts that inspections do not halt production and can be completed in a short period of time, it is reasonable to keep the current once weekly inspection interval.

It is important to note that Equation (4.1) deals with a worst case scenario. If a breakdown failure does not take place, where $b(T)$ is the probability of a breakdown failure, then failure will occur during inspection repair, i.e. 1- $b(T)$, the probability of failure at inspection repair. The best case scenario would be that no breakdown failures would occur and no repairable failures, therefore removing the term E_{damage} from Equation (4.1). A graph illustrating this would be a straight line from day one and increasing at a linear rate up to 41 days, therefore the longer the inspection interval, the greater the cost a failure would be.

4.6 Conclusion

The primary aim of the delay-time analysis concept is to minimise downtime and costs associated with inspection and maintenance activities as well as breakdown costs. The environmental model attempts to quantify the risks in terms of cost associated with a failure resulting in danger to humans and damage to the environment.

In chapter 3 the results of applying delay-time analysis looked at optimising the inspection interval by minimising downtime D(T), minimising costs C(T) and minimising the environmental impact of failure E(T). The first two terms took mainly historical objective data, but the environmental term required a large amount of subjective input. The parameters for applying the environmental model E(T) were developed from uncertainty and estimates in a random and imprecise way. This methodology has attempted to address this uncertainty by using fuzzy-logic combined with max-min analysis and normalisation to give a quantitative approach to applying delay-time analysis using the environmental model.

The environmental model can be applied to differing industries including environmentally sensitive manufacturing processes and facilities which may pose a danger to human life and to the transportation of hazardous or environmentally damaging waste where a high level of uncertainty in data for estimation exists.

Chapter 5

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

Summary

This chapter has been written in order to apply Bayesian network modelling to a maintenance and inspection department. The primary aim of this chapter is to establish and model the various parameters responsible for the failure rate of a system, using Bayesian network modelling, in order to apply it to a delay-time analysis study. The use of Bayesian network modelling allows certain influencing events to be considered which can affect parameters relating to the failure rate of a system. Bayesian network modelling also allows these influencing events to change and update depending on the influencing data available at any given time, thus changing the failure rate or probability of failure. A methodology has been developed and applied to a case study in order to demonstrate the process involved.

5.1 Introduction

When using delay-time analysis to develop a maintenance or inspection model, the need for both relevant and accurate data is vital to the success of the task. The information required in order to carry out such a modelling exercise is gathered from historical data and/or from expert judgement. This information is used to calculate the variables needed to apply delay-time analysis. A detailed definition of each parameter required is given in section 3.3.3 which includes:

- Average downtime due to inspection, d.
- Average downtime for a breakdown repair, d_b.
- Arrival rate of defects per unit time, k_f.
- Failure rate λ (1/MTBF).

Looking at the variable failure rate λ (1/MTBF), the information required to populate this is usually based on statistical averages. For example, if a machine or piece of equipment has experienced 10 breakdowns over a period of 1 year this would result in a failure rate of 0.027 failures/day (MTBF 37 days). To further expand on this example, suppose 70% of the breakdowns occurred during the first 3 months of operation, with only 1 breakdown experienced during the last 2 months of operation. Calculating these figures into failure rates highlights the inadequacy of relying on averages when gathering data of this type (Aven and Sandve (1999)). Specifically, the failure rate for the first 3 months is that of 0.077 failures/day (MTBF 13 days) but the failure rate for the last 2 months is 0.016 failures/day (MTBF 63 days). Although the average failure rate of 0.027 failures/day (MTBF 37 days) is correct for average breakdowns it may not be adequate to portray the actual situation. Continuing with this example, there may be a number of influencing factors that have been responsible for the varying failure rates over the 12 month period. For example, poor reliability of equipment may be encountered due to incorrect installation. Conversely, improvements in the design of the equipment may improve the reliability of the equipment. Other typical influencing factors for this example might include:

- Poor initial implementation of equipment.
- Improvements in inspection procedure.
- Improvements in maintenance personnel training.
- Renewal of key components.
- Changes to inspection intervals.

A modelling technique capable of appreciating the differing influencing factors which could affect an event or variable is that of Bayesian network modelling. Bayesian network modelling is a simple mathematical formula for calculating conditional and marginal probabilities of a random event. Conditional probability is the probability of an event given the occurrence of an influencing event, whereas marginal probability is the unconditional probability of an event. Bayesian network modelling can also deal with subjective probability, which may represent the degree of belief from an expert, and apply it in a precise and relevant manner.

5.2 Applications of Bayesian network modelling

The use of Bayesian network modelling is wide-ranging, covering a multitude of industries and applications. The nature of Bayesian network modelling offers a flexible solution to problems, allowing incremental adjustments to influencing variables and probabilities. This section will examine several relevant case studies in order to demonstrate the varying uses and applications, highlighting both the benefits as well as the drawbacks when using Bayesian network modelling.

The use of oil tankers in the shipping industry is common, where safety is of paramount importance. One of the main risks is that of collisions between tankers and FPSO (floating production storage and offloading) vessels. FPSOs are used when an oil platform is in a remote or deepwater location where seabed pipelines are not cost effective. The process involves pumping oil from the oil rig, transferring it to the FPSO then onto an oil tanker. Numerous collisions between FPSOs and oil tankers have occurred in the North Sea in recent years (Chen & Moan (2002)). A study was carried out examining system safety of FPSOs using Bayesian network modelling techniques (Eleye-Datuba (2005)). The study examined the transfer of oil from an FPSO to an oil tanker. Collision rates were established relating to the varying ways a collision may occur. A fault tree

analysis (FTA) was carried out in order to estimate the frequency of collisions for an FPSO, with additional information gathered from statistical reports. A Bayesian network model was then created to model the scenario using *Hugin* software. The model developed gave two influencing nodes: 'shuttle tanker' and 'support vessel' with one influenced node 'collision-FPSO', with both influencing nodes connecting to the node 'collision FPSO'. The model was run, giving figures of 5% probability of 'impact' and a 95% probability of 'no-impact' for 'collision FPSO'. Given the flexible nature of Bayesian network modelling, a scenario was then initiated in the model whereby the probability of impact was increased to 100%. The probability of loss of shuttle tanker went up from 7% to 50% with the support vessel failure probability rising from 24% to 65%. Given this scenario, several nodes were added including oil spillage, explosion and human injury. The importance of this is that given a certain event happening (100% probability) other factors either influencing or influenced by the event can be considered in the overall risk analysis. For this example these may include weather conditions, spillage of oil, flooding and human error, although human error may be considered to have an influencing effect on most industries in one way or another.

An important aspect to consider when developing Bayesian network models is the complexity of the model. The model can describe complex problems by generating information about their structure, giving an understanding of the system structure (Abad-Grau and Arias-Aranda (2006)). Given this, an important attribute of Bayesian network modelling is its ability of coping with a system of high complexity through modularity. This is achieved by splitting the problem into smaller problem network models, which are solved separately helping to acquire solutions to the larger problem (Pearl, (1988)). The use of Bayesian network modelling for optimising preventative maintenance modelling was developed to a limited amount in a petrochemical case study (Percy and Kobbacy (1996)). Preventative maintenance is a maintenance activity aimed at reducing the occurrence and/or severity of failure in a system. In contrast to preventative maintenance is that of corrective maintenance. With corrective maintenance

repairs are carried out only after failure has taken place in the system. This study looked at analysing the renewal process with exponential distribution times to failure using Bayesian modelling. The use of Bayesian modelling allowed the prediction of the probability distribution for downtime and the amount of corrective repairs necessary which ultimately gave a cost per unit time. There was no comparison drawn between this study and that of traditional methods to establish a failure probability distribution. It did however highlight the need for inclusion of prior knowledge using a Bayesian methodology in order to derive probability distributions. This served to reduce the reliance on estimation of parameters which traditionally takes place, allowing optimal decisions regarding maintenance intervals to be established.

Several assumptions were made in this study including: each maintenance activity having the same downtime duration and each corrective repair having the same downtime duration. These assumptions may be too restrictive in reality but this example illustrates the use of applying Bayesian network modelling to establish a probability distribution to enhance another maintenance modelling exercise.

A case study looking at reliability assessment during equipment development of a weapon system using a Bayesian approach has also been carried out (Ke and Shen (1999)). This paper looked at an integrated Bayesian approach to assess equipment reliability during the development cycle. The integration process took information relating to the engineering knowledge available and integrated this with statistical results gathered from the testing program giving a true quantitative viewpoint. Bayes' theorem was applied to evaluate the reliability achieved by updating the prior distribution, showing the current reliability. This information was used to assess and evaluate the effectiveness of design changes that were previously carried out. This evaluation gave the management valuable information relating to design changes, aiding the decision process of whether the design is satisfactory or whether further corrective action relating to the design is required.

Given these varying applications of Bayesian network modelling in the engineering industry, a methodology has been developed in the following section to analyse the failure rate of a component.

5.3 Methodology

Applying Bayesian network modelling to a parameter, namely failure rate λ, of delay-time analysis requires the development of a methodology. This methodology will serve to improve the accuracy of the delay-time model by improving the understanding of the events responsible for failure. It will also, given the nature of Bayesian modelling, give a continuing accuracy of failure rate given changes to certain influencing factors. The methodology will include the following stages:

- Gather available information.
- Establish nodes with dependencies.
- Create conditional probability table (CPT) and prior probabilities for each node.
- Normalise probability values.
- Propagate evidence.
- Generate posterior probabilities.

5.3.1 Gather available information

When gathering information relating to the failure rate of a component, it is vital to establish the type of data that is required. This data may come in the form of historical data i.e. maintenance reports, databases, etc., and/or from expert opinion, i.e. through the use of questionnaires, brainstorming, etc. When utilising Bayesian network modelling, expert opinion becomes a valuable asset when

developing the nodes and conditional probability table (CPT) information for the model. Often values will need to be assigned through expert judgement due to the lack of objective data available. As objective data becomes available, this can then update or replace any estimates that have been entered into the model using subjective means. Influencing factors relating to failure of equipment may cover aspects such as:

- Age of component or equipment.
- Life expectancy of component or equipment.
- Inspection interval.
- Inspection success rate.
- Competence of inspection.
- Competence of maintenance / inspection personnel.

Once the relevant data has been gathered relating to failure rate both from objective means and from subjective means, influencing nodes or events need to be established together with dependencies for each node.

5.3.2 Establish nodes with dependencies

The constructing of a Bayesian network begins with the graphical representation of the nodes (event or variable) and their dependencies (indicated with an arc) to each other. This helps to develop the detail of the network as well as simplify the causal assumptions which are often difficult to express through mathematical notation (Pearl (2000)). The influencing nodes relating to the failure rate of a component can vary depending on the equipment or process in question. The influencing factors, as discussed in the previous section, may also need to take into account equipment or component failures of lesser or seemingly insignificant components which have a knock-on effect to the overall failure rate. Often influencing factors can carry a differing weighting from each other

depending on the circumstances surrounding failure. For example, the influence of human interaction will figure more prominently in a labour intensive process or production line than a process with a high degree of automation.

5.3.3 Create CPT and prior probabilities for each node

Having established the influencing nodes responsible for failure together with the dependencies, a CPT can now be developed for each node or event. Theoretically, the CPT may be populated using historical evidence, expert judgement or a combination of the two. A common criticism of the Bayesian approach is that it requires too much information in the form of prior probabilities (Yang et al. (2008)). This information is often difficult, if not impossible, to directly obtain in its practical applications. It therefore requires appropriate transformation of the initial data into a 'legal' format, which can be accepted and accommodated by Bayesian reasoning. For example, in maintenance planning, historical data which is normally collected and expressed in the form of failure rates/frequency λ based on time units (i.e. MTBF) may sometimes need to be converted into failure probabilities p through setting up the worst marginal frequency criterion $\vec{\lambda}$. The criterion represents the extreme failure frequency rate that an industry can tolerate in practice before defining the total failure of the equipment. Specifically speaking, the conversion can be symbolised as:

$$p = \lambda \times \vec{\lambda}^{-1} \tag{5.1}$$

If any failure frequency is larger than $\vec{\lambda}$, its corresponding failure probability will be defined as 100%. The result of applying this transformation rule is to give the nodes a prior probability. As previously mentioned, nodes with no dependencies i.e. no parents, have marginal probabilities, dependant nodes i.e. child nodes, have conditional probabilities.

5.3.4 Normalise probability values

Normalisation of probability values is required to be non-zero with each condition of a CPT having a value between 0 and 1 and a combined value for each CPT of 1. The software used in this study (*Hugin*) automatically normalises any values entered.

5.3.5 Propagate evidence

Results are established through the propagation of the Bayesian model, it is vital to understand that although the graph is acyclic entered evidence propagates in both directions. A useful additional aspect of the *Hugin* software is that it allows the user to 'lock in' evidence of a node when propagating the model, thus allowing unchanging evidence to remain whilst allowing other variables to update.

5.3.6 Generate posterior probabilities

The generation of posterior probabilities is the results of running the model after evidence is entered to improve the state of knowledge.

5.3.7 Validation of the model

Validation is an important aspect of this methodology as it will provide a reasonable amount of confidence to the results of the model. In this particular study a sensitivity analysis for partial validation of the model has been developed, the following three axioms must therefore be satisfied:

Axiom 1. A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of the child node.

Axiom 2. Given the variation of subjective probability distributions of each parent node, its influence magnitude to the child node values should keep consistency.

Axiom 3. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the values should be always greater than the one from the set of x-y ($y \in x$) attributes (sub-evidence).

5.4 Case study

In order to demonstrate the above methodology a case study of a factory producing carbon black in the UK is given. A detailed description of the factory can be found in section 3.4. There is a detailed description of the impact of failure of a filter bag on the environment in section 3.4.1. The costs relating to the failure of a filter bag both directly and indirectly can also be found in section 3.4.2.

This brief introduction to the production of carbon black, as described in chapter 3, serves to highlight the importance of preventing failure of a filter bag. As previously discussed in the introduction, delay-time analysis is used to establish a maintenance model which will give an optimal inspection interval based on reducing downtime. A key parameter of delay-time modelling is the parameter of failure rate λ. This case study will use Bayesian network modelling to improve the accuracy of the parameter failure rate.

5.4.1 Gather available data

Failure of a filter bag can have several factors that can contribute to failure. As is the case with most components, the age of the filter bag is an important factor when considering potential failure. The closer the filter bag is to the end of its life expectancy, the higher the probability of a failure occurring. There are a number of characteristics that occur due to age. Firstly, the colour of the waste gas will change gradually over a number of weeks, this is due to the higher content of carbon black being burnt. Secondly, the filter bag will become more brittle with age therefore being more susceptible to rupture due to high temperature spikes. Monitoring of and control of the filter bag temperature is a vital element when considering bag failure. If the temperature in the filter bag is too low, then corrosion of the bag takes place rapidly due to condensation from the sulphur. The sulphur moves from a gaseous state to a liquid state creating sulphuric acid, the sulphuric acid, thus leading to rapid corrosion and in turn bag failure. Too high a temperature or high temperature spikes in the bag results in burning of the bag, which in turn renders the bag brittle. Also, high temperature spikes have a higher probability of causing failure, this failure probability further increasing as the age of the filter bag increases. An important influence to consider is that of operator competence. In this case study it is not given the same influencing weight due to the level of automation of the system, but it must be considered if only at a reduced level. In other industries this would generally take equal importance, with greater importance being assigned in a dangerous, labour intensive industry, such as the oil or gas industry. The final contributor to failure of a filter bag is equipment failure. The fundamental process of a filter bag is:

- The bag is filled with carbon black where it forms on the inside of the bag which increases the pressure.
- The bag is then decompressed thus crushing the bag slightly, this decompression releases the carbon black from the bag and into a loading compartment beneath the bag.

- The bag is then refilled with carbon black thus commencing the process all over again.

Failure of the bag to decompress will result in more and more carbon black being fed into the bag, this eventually leading to tearing the bag due to over filling. Given this information, nodes can be established with relevant dependencies.

5.4.2 Establish nodes with dependencies

As a result of gathering relevant information relating to the failure of a filter bag, the nodes that have been established which have an influencing factor to the failure of a filter bag are:

- Operating temperature.
- Age of filter bag.
- Competence of operator.
- Equipment failure.

A simple influence diagram illustrating the factors which may contribute to the failure of a filter bag is illustrated in figure 5.1.

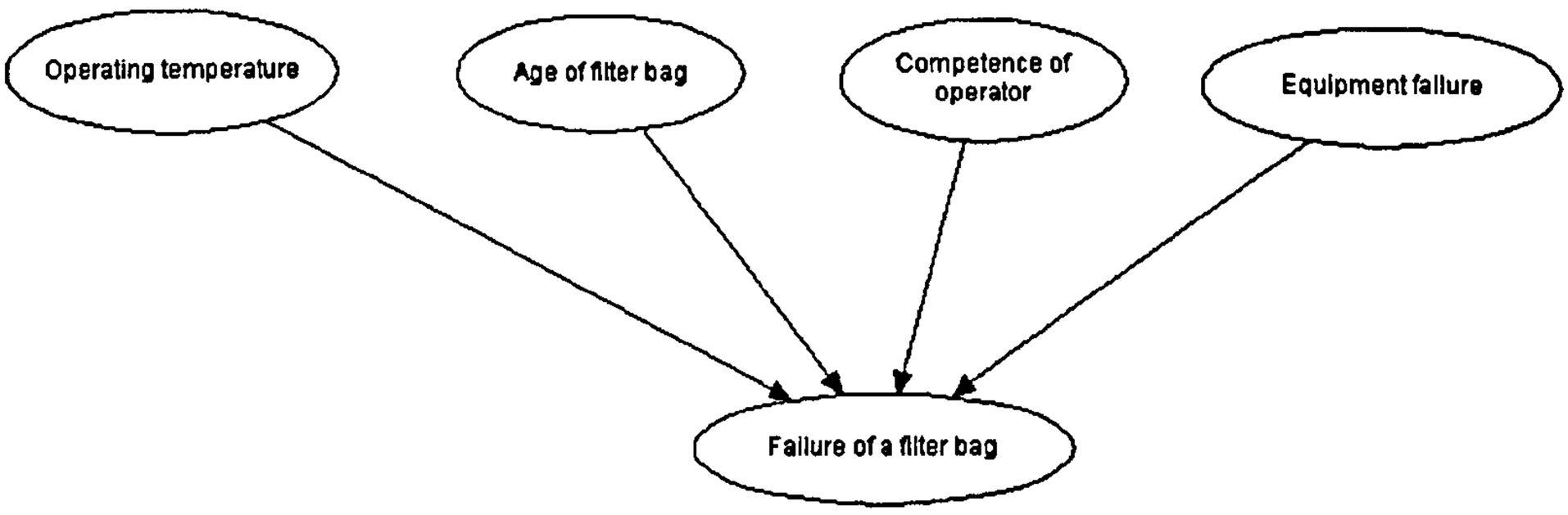


Figure 5.1. A Bayesian network relating to the failure of a filter bag.

With each node having an influencing factor on the failure of a filter bag, it is important to distinguish between the impact 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. The 'competence of operator' is reduced in importance partly due to the level of automation of the systems in place as well as the lack of dependency on one individual person. If this case study were to look at the downtime of the production facility instead of failure of a filter bag, then competence of operator would be considered a major influencing factor, due to operator error representing 20% of production downtime. The data gathered as well as the expert judgement given has reflected this and will be conveyed in each CPT.

5.4.3 Create CPT and prior probabilities for each node

The next step is to establish a CPT for each node. Information has been gathered from historical data and from expert judgement. The CPT for each node is illustrated in figure 5.2.

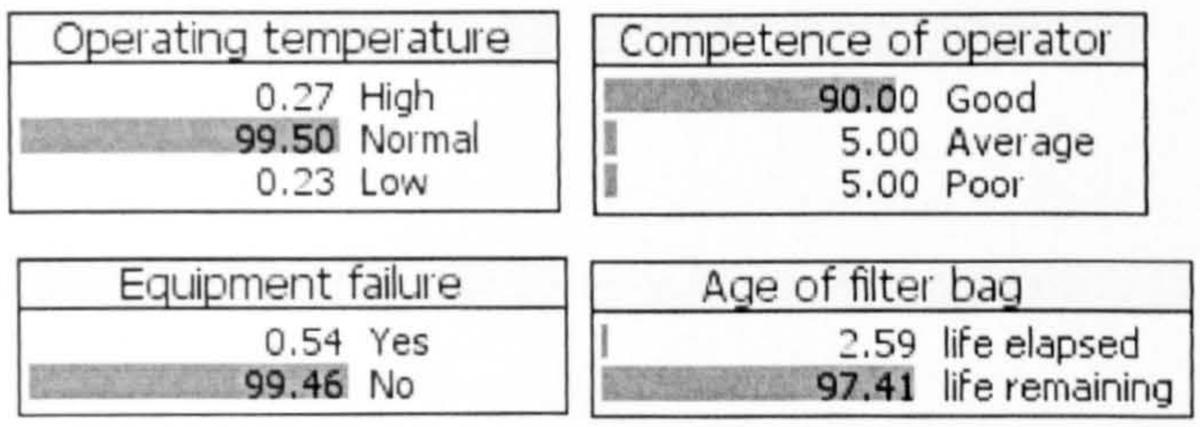


Figure 5.2. CPT for each influencing node relating to 'failure of a filter bag'.

As illustrated in figure 5.2, each CPT has been populated using mainly historical data as well as expert judgement. The node 'Operating temperature' represents the probability of the system over the last 12 months to run either at a high

temperature (0.27%) or at a low temperature (0.23%) given that $\vec{\lambda}$ 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 (5.1), gives:

$$p = \lambda \times \vec{\lambda}^{-1} = 1 \text{ failure} / 365 \text{ days} \times (1 \text{ failure} / \text{day})^{-1} = 0.27\%.$$

Applying Equation (5.1) to this case study allows the use of failure data to become available as a probability for use in the Bayesian network model. Equation (5.1) accepts 1 failure per day, which will equate to 100% failure, as tolerable for this model. Failures exceeding this figure would still be regarded as 100% failure as anything higher than 1 failure per day is regarded as unacceptable.

The node for 'Equipment failure' is established using the same logical premise which is used for 'Operating temperature'. The frequency of equipment failing is twice over the same period of 12 months. Applying Equation (5.1) to this information gives:

$$p = \lambda \times \vec{\lambda}^{-1} = 2 \text{ failures} / 365 \text{ days} \times (1 \text{ failure} / \text{day})^{-1} = 0.54\%.$$

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. An example could be if the age of the filter bag is 100 days old, it has been in operation 7.8% of its life expectancy, life remaining would therefore be 92.2% (100% - 7.8% = 92.2%). 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 only becomes a main contributor to failure when combined with other influencing nodes, for example, high temperature spikes. Figure 5.3 illustrates the CPT of 'Failure of a filter bag' given all influencing factors/probabilities.

Operating temperature	High											
Equipment failure	Yes						No					
Age of filter bag	life elapsed			life remaining			life elapsed			life remaining		
Competence of operator	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor
Failure	22	27	32	17	22	27	20	25	30	15	20	25
Working	78	73	68	83	78	73	80	75	70	85	80	75

Operating temperature	Normal											
Equipment failure	Yes						No					
Age of filter bag	life elapsed			life remaining			life elapsed			life remaining		
Competence of operator	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor
Failure	2	4	6	2	4	6	0	1	2	0	1	2
Working	98	96	94	98	96	94	100	99	98	100	99	98

Operating temperature	Low											
Equipment failure	Yes						No					
Age of filter bag	life elapsed			life remaining			life elapsed			life remaining		
Competence of operator	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor	Good	Average	Poor
Failure	4	6	8	6	8	10	2	4	6	1	2	3
Working	96	94	92	94	92	90	98	96	94	99	98	97

Figure 5.3. CPT for 'Failure of a filter bag'.

It is clear to see how quickly a Bayesian model can become complicated given only four influencing events. In figure 5.3, 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 CPTs 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.

5.4.4 Propagate evidence

The propagation of evidence examines several different scenarios and combinations of events taking place (i.e. 100% probability). Propagation serves to highlight a problematic area that may require closer scrutiny should a particular event take place. With regard to this case study, taking into account all of the prior probabilities, the failure probability of a filter bag is estimated to be 0.21%. Applying equation (5.1) to this failure probability makes it possible to transfer the failure probability to failure rate λ. A failure probability of 0.21% applied to equation (5.1) will then equate to a failure rate λ of 0.0021 failures/day or MTBF of 476 days. This is illustrated in figure 5.4.

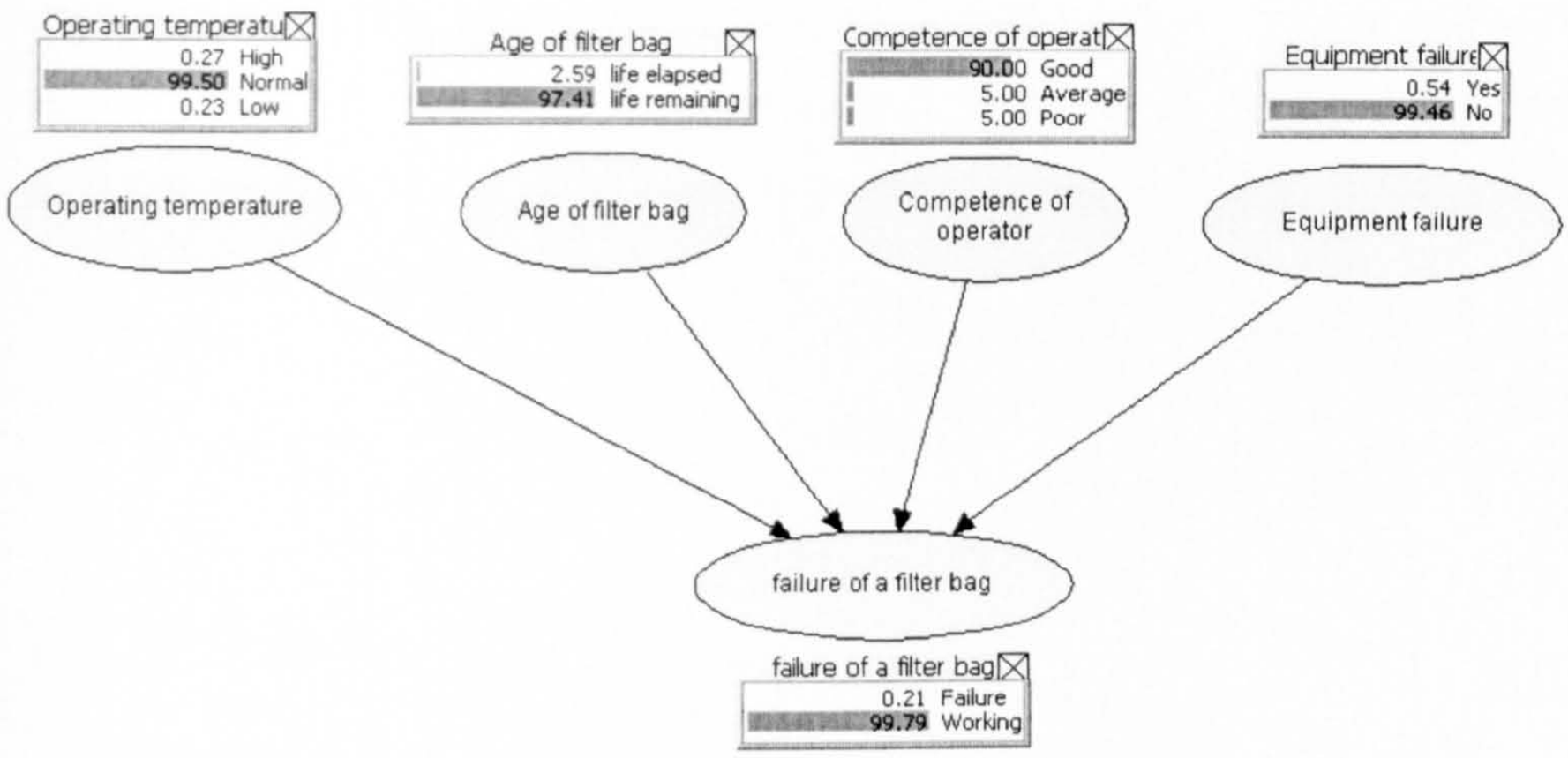


Figure 5.4. Prior probability of 'Failure of a filter bag'.

With the age of the filter bag remaining at 34 days, this evidence may be locked in the model, meaning that this parameter will not change given other changes in the

model. Having locked the age of the filter bag, a useful scenario that can be 'run' in this model is to simulate a high temperature spike, illustrated in figure 5.5.

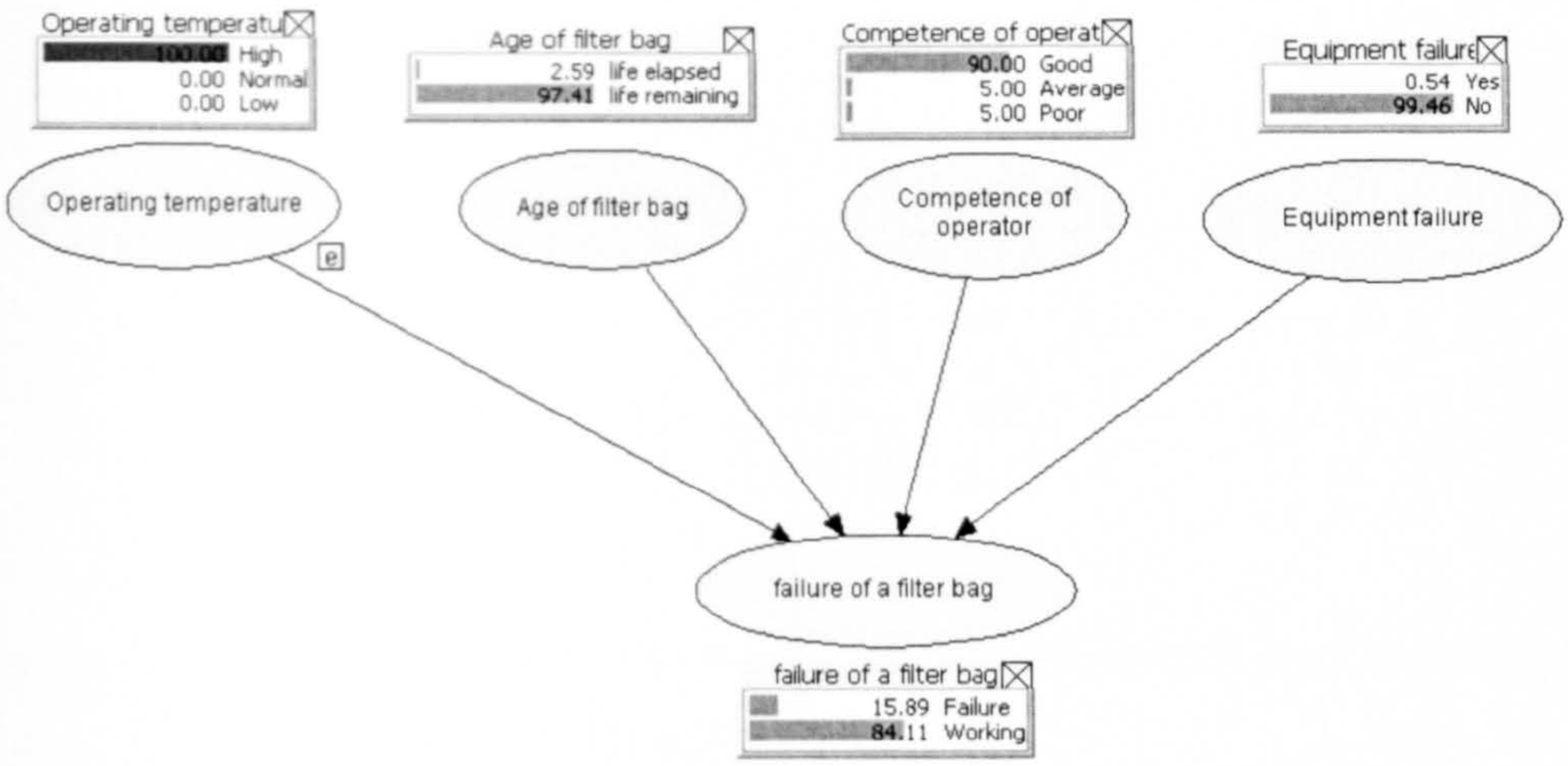


Figure 5.5. Probability of 'Failure of a filter bag' given a high temperature spike.

From the scenario, illustrated in figure 5.5, a high temperature spike increases the failure probability to nearly 16% (MTBF 6.3 days). This is the single biggest 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, this scenario is illustrated in figure 5.6.

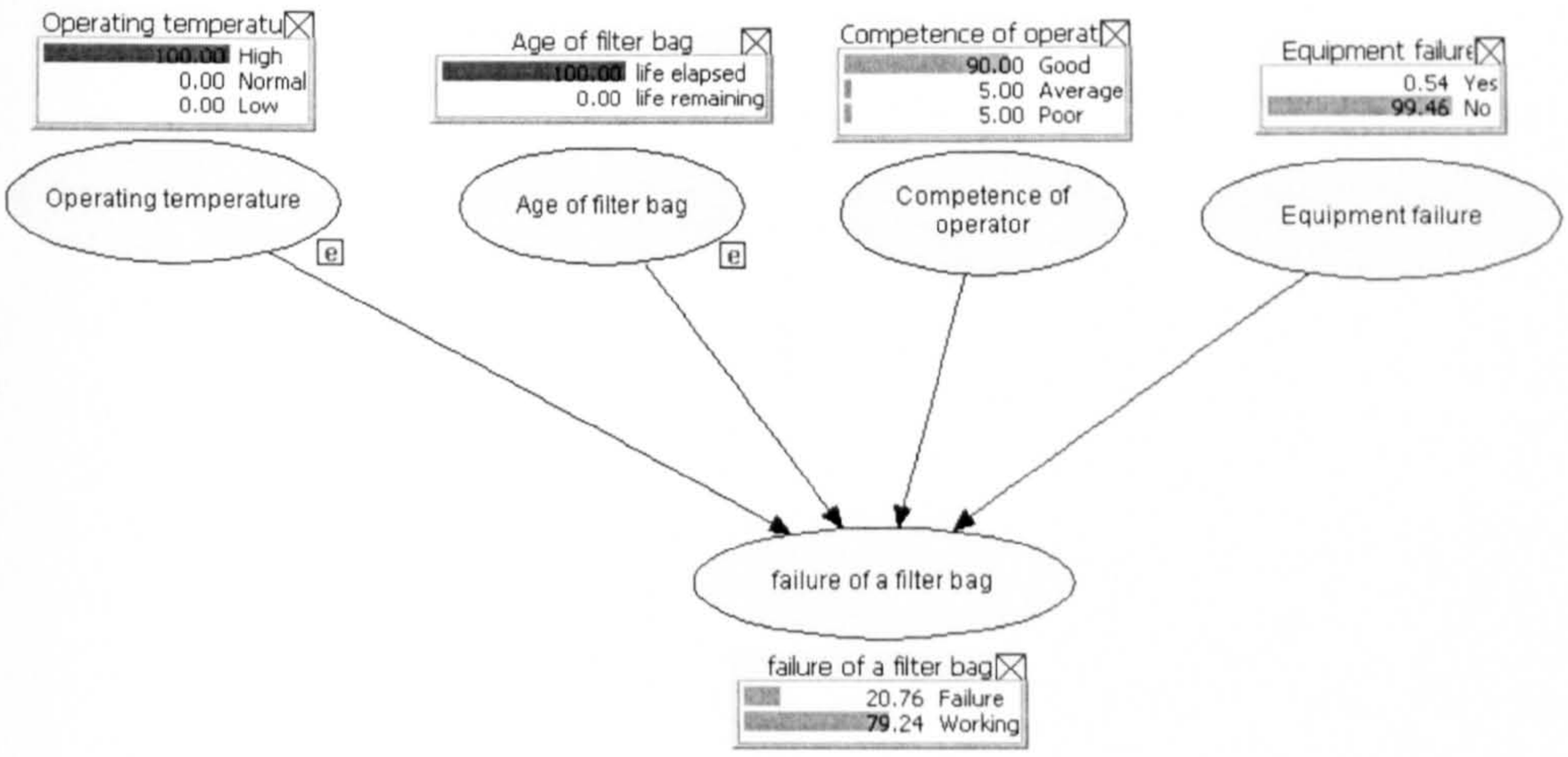


Figure 5.6. Probability of 'Failure of a filter bag' given both a high temperature spike and aged filter bag.

As illustrated in figure 5.6, given the event of a high temperature spike together with the age of the filter bag (100% 'current age'), the probability of failure of a filter bag raises to 20.76% (MTBF 4.8 days). The operating temperature for this particular process is monitored closely but this scenario highlights the implications should a problem arise relating to operating temperature. Examining the scenario of a third additional event taking place, 'competence of operator' (i.e. 'poor' 100%) gives a further increase to that of 30.01% for the probability of failure (MTBF 3.3 days), illustrated in figure 5.7.

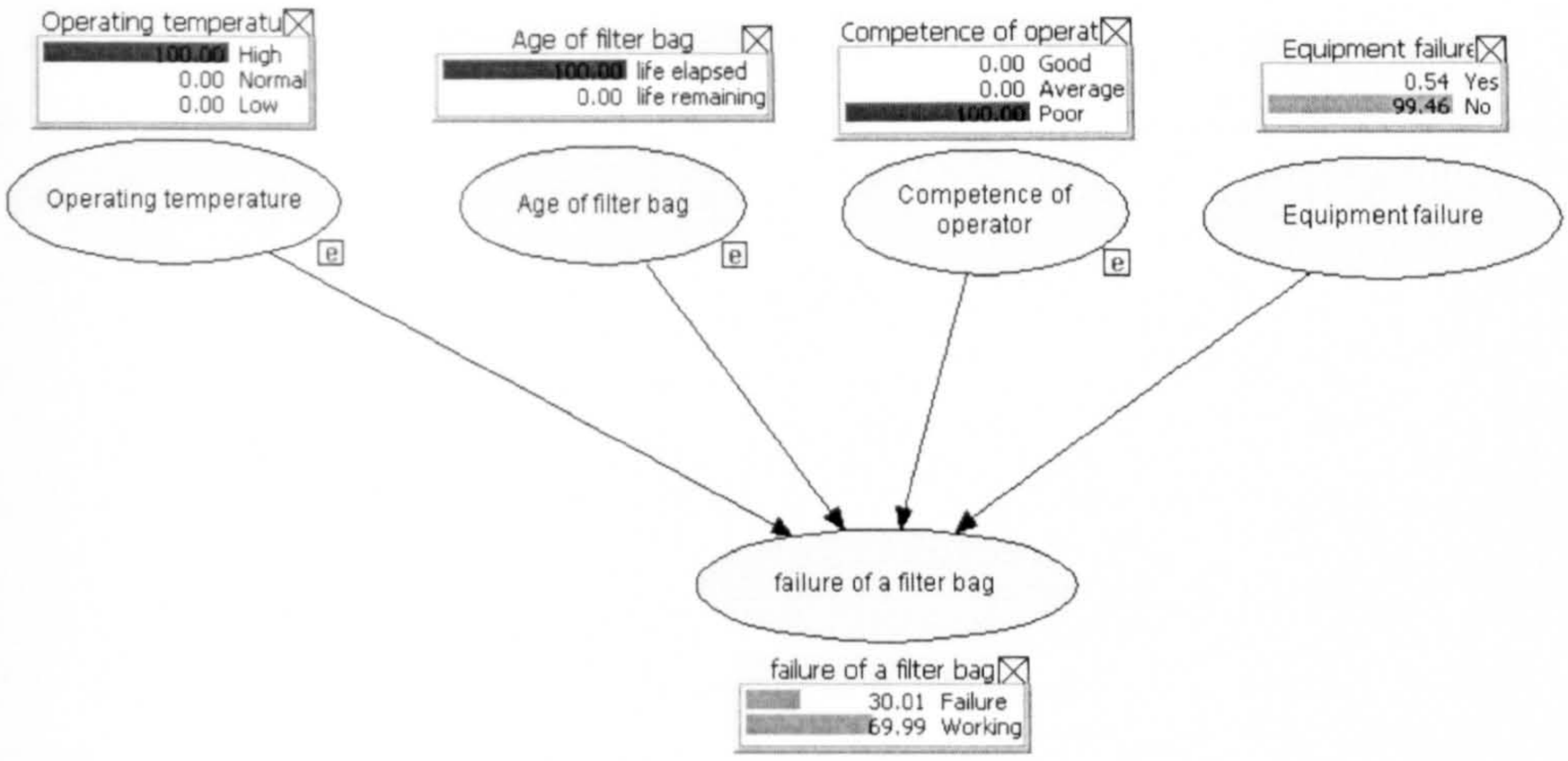


Figure 5.7. Probability of 'Failure of a filter bag' given a high temperature spike and aged filter bag together with 'poor' competence of operator.

The increase in probability of failure of a filter bag illustrates a significant jump of 45% from 20.75% to 30.01%. It is worth noting that although 'competence of operator' has been given a reduced level of importance compared to the other influencing factors, the change of 'competence of operator - good' has gone from 90% to 0% and 'competence of operator- poor' has gone from 5% to 100%.

Incorporating the final influencing factor 'equipment failure' illustrates an increase of almost 7% for failure of a filter bag, moving from 30.01% to 32% (MTBF 3.1 days). This scenario is illustrated in figure 5.8.

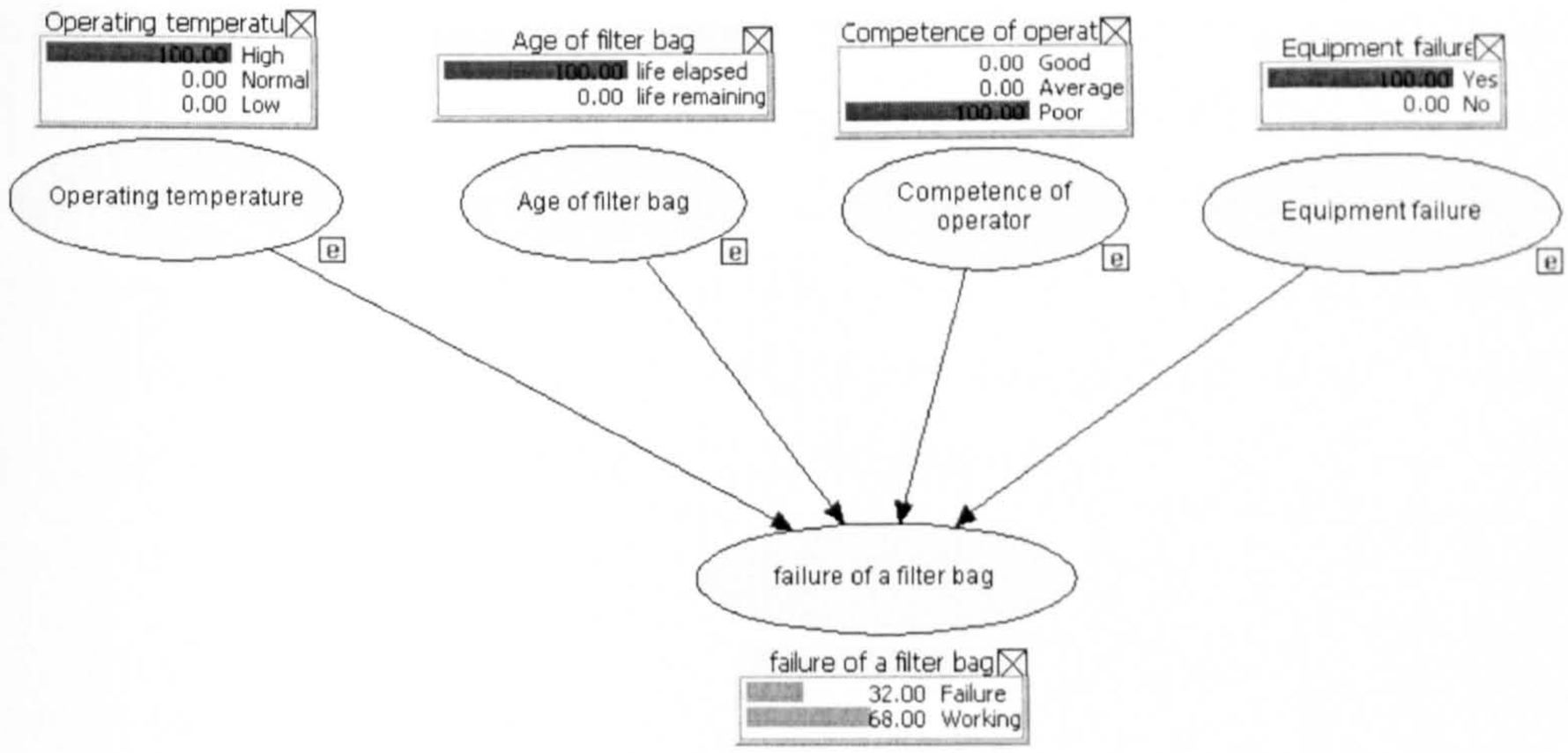


Figure 5.8. Probability of 'Failure of a filter bag' given the probability of all influencing factors taking place.

This final scenario highlights that although equipment failure is considered to be an insignificant influence in comparison to a high temperature spike, it serves to point out that it does possess an influence, albeit a small one. The final scenario to look at will be to see the effect of failure of a filter bag ('failure' 100%) on the influencing parameters. This will serve to obtain possible areas for closer inspection. The model showing failure of a filter bag is illustrated in figure 5.9.

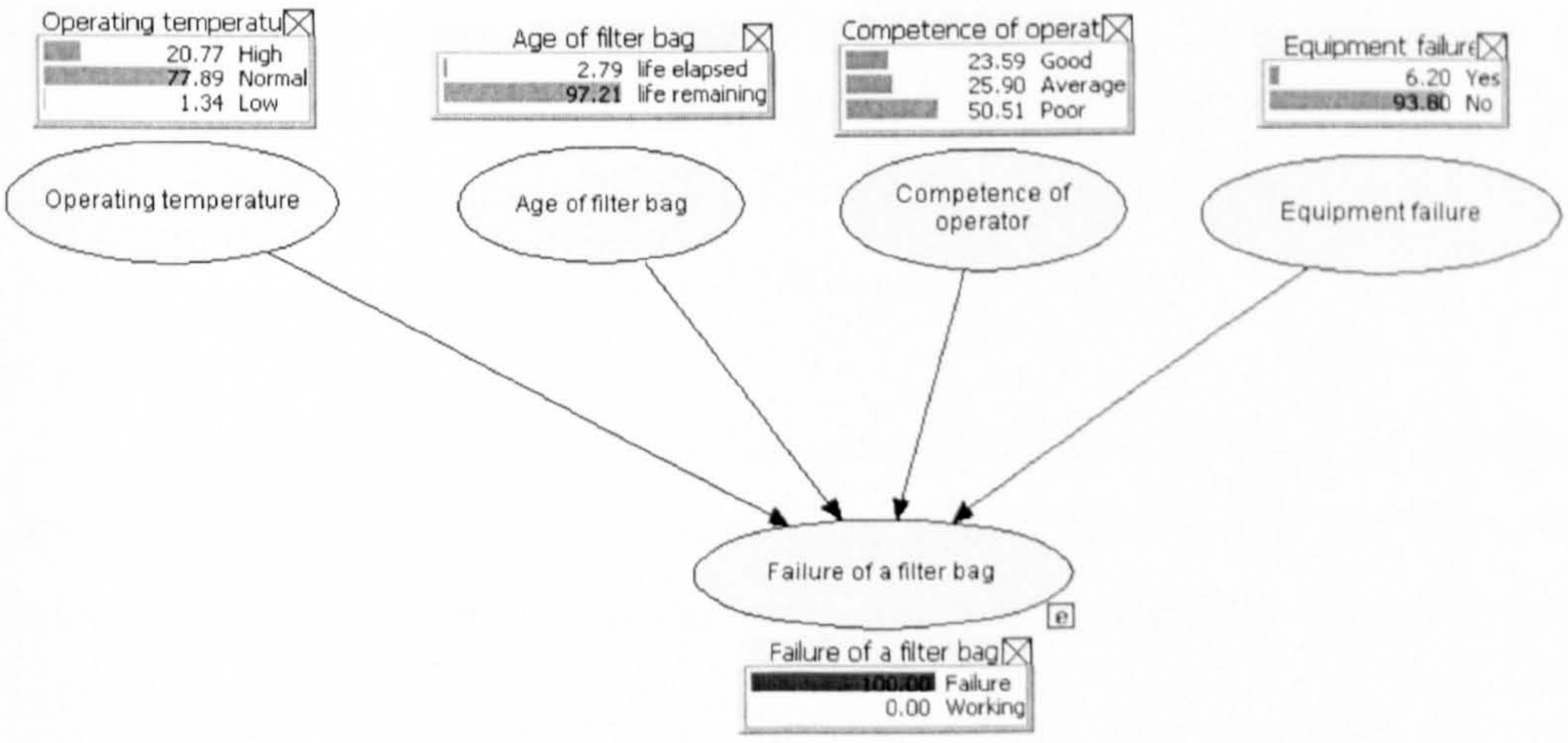


Figure 5.9. Model illustrating when the failure of a filter bag takes place.

This scenario has given an insight into the possible causes that may be responsible should the failure of a filter bag take place. 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.

5.4.5 Validation of model

A sensitivity analysis has been carried out in order to give a partial validation of the model. The model must satisfy the three axioms described in section 5.3.7. Examination of the model, illustrated in figure 5.5, reveals that when the 'operating temperature' is set to 100% 'high' this results in a revised failure probability of 15.89% from 0.21%. When the 'operating temperature' is set to 100% 'high' and the 'age of the filter bag' is set to 100% 'current age' this resulted in a further increase in the failure probability of a filter bag, illustrated in figure 5.6. Figure 5.7 illustrates identical changes to that of figure 5.6 but with the addition of 'competence of operator' set to 100% 'poor', this again resulted in yet a further increase in the failure probability of a filter bag. Finally, figure 5.8 illustrates the changes from figure 5.7 with the addition of 'equipment failure' set to 100% 'yes', resulting in a further increase in the failure probability of a filter bag. The exercise of increasing each influencing node satisfies the axioms stated in section 5.3.7, thus giving a partial validation to the model.

This case study will use the Bayesian network model to establish the failure of a filter bag for use with 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.

5.5 Compare results with previous study

Chapter 3 examined the process of producing carbon black. It gathered objective information from historical records and applied subjective expert judgement where required. This information was then applied to a maintenance model using delay-time analysis to establish a downtime model. The same historic data as well as the same expert judgement has been used for this case study. The aim of this case study is to replicate the same delay-time analysis but with the parameter failure rate λ established using Bayesian network modelling instead of statistical averages as previously used. All other parameters used for this study have remained unchanged, namely:

- Downtime for an inspection, d - 0.1 days.
- Downtime for breakdown repair, d_b - 7 days.
- The arrival rate of a defect, k_f - 0.28 per day.

The Bayesian model, illustrated in figure 5.4, has established that the probability of failure of a filter bag is 0.21%. The use of Equation (5.1) allows this failure probability to be converted into a failure rate, giving the failure probability a failure rate λ of 0.0021 failures/day or MTBF 476 days. The previous study calculated the parameter failure rate λ to 0.0009 failures/day (MTBF 1095 days). A useful way of looking at the information gathered in the Bayesian model would be to input the original failure rate of the filter bag (failure rate λ 0.0009 failures/day or failure probability 0.09%) into the model. This will serve to identify the changes which take place to the influencing parameters, this is illustrated in figure 5.10.

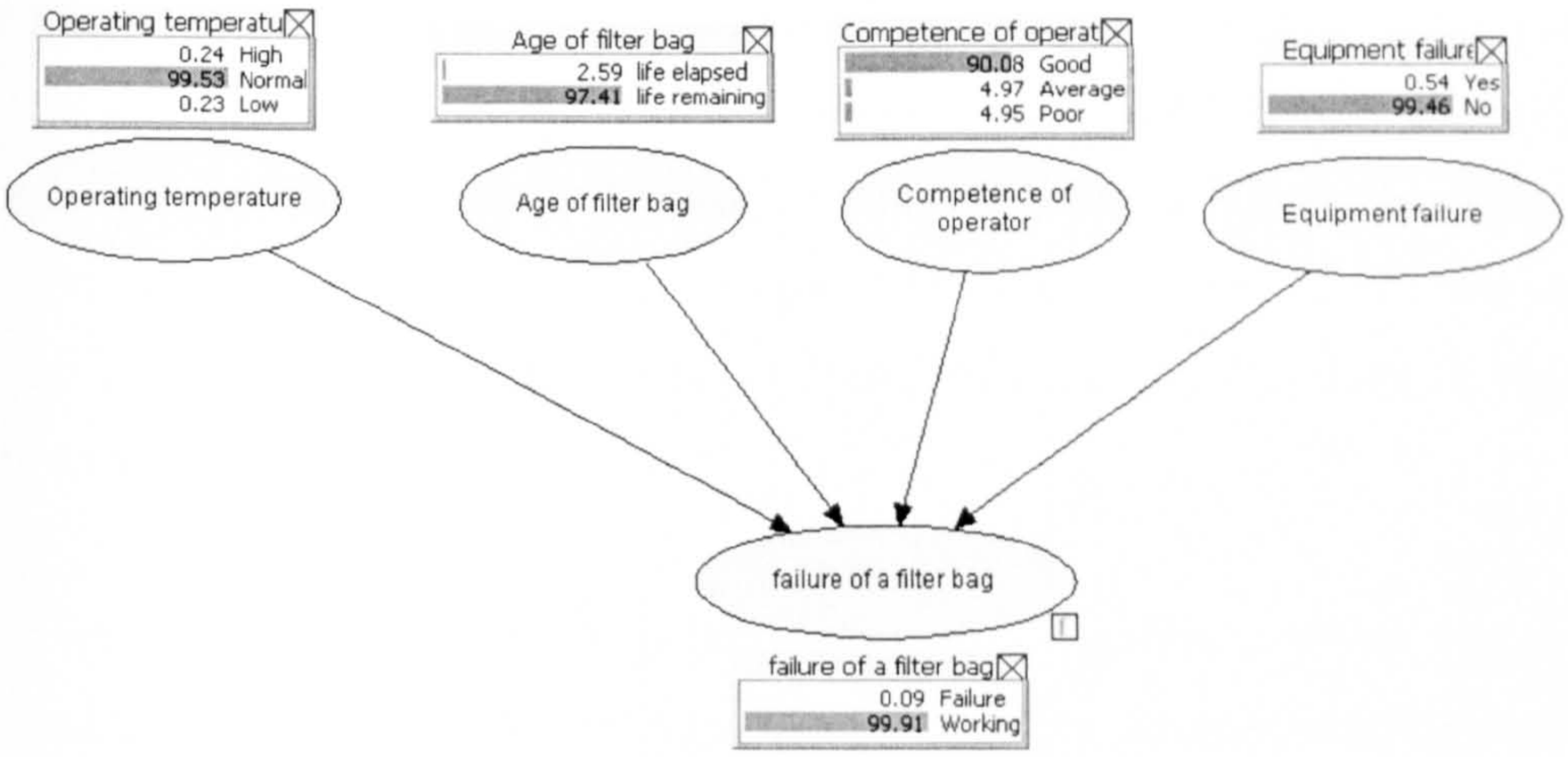


Figure 5.10. Probability of 0.09% 'Failure of a filter bag'.

As illustrated in figure 5.10, the probability of failure of a filter bag has been changed from 0.21% to 0.09% (0.09% equivalent to failure rate λ 0.0009). This adjustment has altered the influencing parameters by what appears to be an insignificant amount. The change in each parameter is more significant when the change is calculated in relative terms. Looking firstly at the influencing parameter 'operating temperature', there is a nominal increase in 'normal' of 0.03% but a significant change of 'high' from 0.27% to 0.24%, this decrease equating to a change of around 11%. The parameter 'age of filter bag' has been locked at 34 days so that no change in the age can take place. There is also no change in the parameter 'equipment failure'. This is due to the influence regarded as low both from failure data and from expert judgement. The parameter 'competence of operator' again appears to have had only an insignificant amount of change but closer inspection challenges this. Competence 'good' increased nominally, average decreased by 0.06% and 'poor' decreased by 1%. The changes to this parameter are small but viewed as a whole must be considered. Overall the failure rate has been established, taking into account the four influencing parameters outlined in section 5.5.4, as 0.0021 failures/day or MTBF 476 days. The original estimate taken from statistical averages based failure rate λ on 1 failure of a filter bag over a 3-year period, 0.0009 failures/day or MTBF 1095 days. This illustrates

a distinct lack of accuracy when relying on statistical averages when compared to factual historical data supported by expert judgement. Establishing clear influences for the failure of a filter bag can also give a greater depth of understanding as to what may cause failure. The historical data used in this study is relevant to the influencing parameters established and can therefore be applied with confidence.

This differing of one parameter when applying delay-time analysis may seem an insignificant adjustment initially. This seemingly insignificant adjustment becomes noticeable when a direct comparison is considered, this comparison is illustrated in figure 5.11.

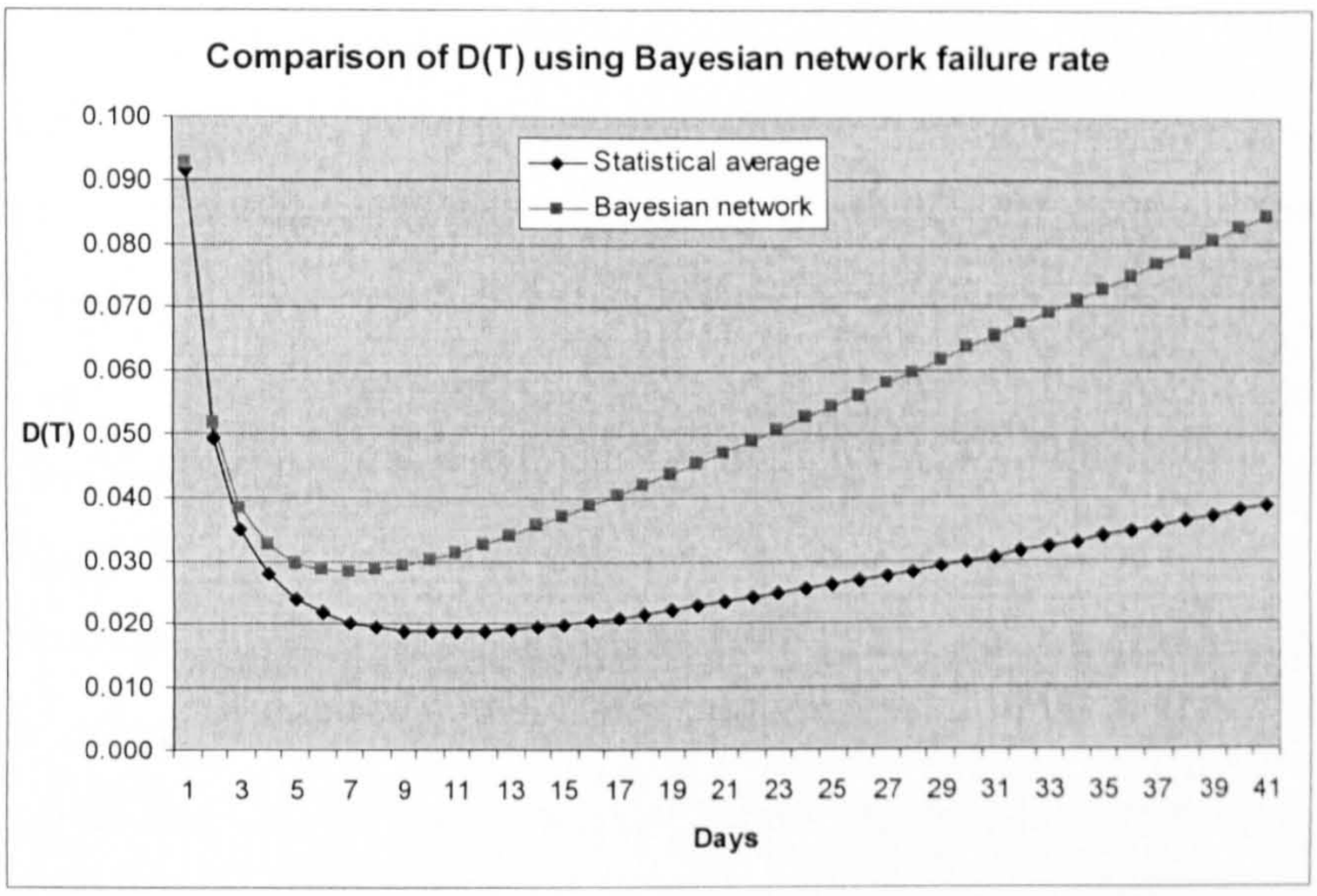


Figure 5.11. A comparison of D(T) using a Bayesian network calculated failure rate λ

When applying the improved figure for failure rate / MTBF to the original delay-time analysis a difference in the result becomes apparent immediately. A closer look at figure 5.11 reveals a change in the minimum inspection interval based on minimum downtime D(T). The minimum inspection interval using

statistical averages to calculate the failure rate λ was originally calculated at 11 days. Using Bayesian network modelling to calculate the failure rate to establish an optimum minimum inspection interval reduces this inspection interval to 7 days.

5.6 Discussion

The aim of this chapter has been to apply delay-time analysis, a maintenance modelling technique, to a company producing carbon black. The parameters required to carry out such a study using delay-time analysis come mainly from objective, historical data. The parameter failure rate λ has been previously established using historical data calculated using statistical averages. This method, though, cannot adapt to the ever-changing influences responsible for failures and their effects on equipment or components. Bayesian network modelling was therefore used to counteract this inherent problem.

The Bayesian model in this case study allows relevant information, considered an influencing factor on the failure of a filter bag, to be included. The inclusion of these influencing factors has given a greater depth of understanding to the parameter failure rate λ, resulting in a greater confidence in the overall results of the delay-time analysis. The influencing factors 'operating temperature', 'age of filter bag', 'competence of operator' and 'equipment failure' have been used for this study. The historical data gathered for each influencing parameter together with the expert judgement has been carefully scrutinised and applied to the Bayesian network model.

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 λ. The re-evaluation of the parameter failure rate λ, has reduced the optimum inspection interval from 11 days to 7 days.

5.7 Conclusion

In chapter 3, a case study was carried out to establish an optimal inspection interval using delay-time analysis. The aim of this case study was to minimise maintenance and inspection costs by reducing downtime whilst optimising inspection intervals. Delay-time analysis relies on several parameters in order for it to be effective. One of the parameters, failure rate λ, relies on the manipulation of historical data using statistical averages.

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

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

Chapter 6

Integration of the models developed and discussion

Summary

This chapter will examine the delay-time analysis model developed in chapter 3 of this thesis and attempt to integrate, both the fuzzy set model (Chapter 4) and the Bayesian network model (chapter 5). The discussion in this chapter will centre on the advantages that delay-time analysis can offer a manufacturing company. Part of this discussion, however, will highlight the limitations of delay-time analysis. This chapter will attempt to overcome these possible limitations by introducing and applying the models developed in Chapter 4 and Chapter 5.

6.1 Introduction

Delay-time analysis has been used as a basis for developing inspection maintenance models in many case studies. The application of applying this modelling technique shows an appreciation of many elements which are generally overlooked when attempting to establish an inspection interval. Elements such as inspection times and inspection costs, breakdown times and breakdown costs are all considered as well as the failure distribution function of the component or equipment in question. It is this incorporation of several differing pieces of information that establishes a cost effective inspection interval, which makes delay-time analysis a potentially powerful tool to most maintenance departments.

6.2 Development and limitations of Delay-time analysis

The development of a delay-time model is one which requires information gathered from various sources in order to construct a precise and accurate model. The sources of information may come from historical data such as maintenance reports or failure data. Information may also come from subjective data in the form of expert judgement. This information is generally gathered through the use of questionnaires and/or brainstorming sessions. Regardless of the method of gathering the required information necessary to produce a model, accuracy of data which will bring about confidence in the model, will be of utmost importance to any manufacturing facility.

It is clear from chapter 3 that the information that was gathered and applied, in order to generate a delay-time model for the downtime model D(T) and the cost model C(T), was taken mainly from historical information. The downtime model, D(T) used predominantly objective data, for instance Mean Time Between Failure (MTBF), arrival rate of defects k_f and downtimes due to inspection and repairs. The cost model, C(T) used available data relating to costs of a failure, costs of a breakdown and costs of inspection. The information required for the development of the environmental model E(T), however, relied heavily on a mixture of objective data and subjective data which was gathered from expert judgement. The problem of elicitation of the objective and subjective information had to be overcome in order to have reasonable confidence in the modelling results. The environmental model has a reliance on expert judgement to establish the majority of its parameters. It is this reliance that reveals a possible limitation of the delay-time model.

The difficulty in keeping a consistency between each expert opinion when attempting to establish costs relating to failure of equipment is challenging. The inherent problem resides in an individual's perception and judgement of a given situation. For example, one expert may give a cost relating to the consequences to

human health of a failure as moderately low while a second expert may perceive this cost as significantly higher. These differences may be due to previous life experiences of the individuals. This vagueness and inconsistency will diminish the accuracy of the results as well as the confidence in the modelling process. These inconsistencies highlighted have been dealt with in chapter 4 of this thesis by utilising fuzzy set theory in order to establish these subjective parameters. The use of fuzzy set theory to model these parameters succeeded in overcoming the vagueness of the gathered expert judgement data.

Another limitation, which seems insignificant when first considered, is that of the term failure rate λ (1/MTBF). As previously discussed, this term is established through the gathering of failure data over a period of time and calculated as the number of failures encountered divided by the amount of time in question. In chapter 3, failure rate was established for the case study by simply dividing the number of failures, which was 1, by the amount of time in question, 1095 days (3 years). This equated to a failure rate of 0.0009 or a MTBF of 1095 days. Having produced a delay-time model for the case study in chapter 3 using this failure rate, it became apparent that a slight deviation in failure data can result in a significant change to the failure rate parameter. This change in the failure rate parameter in turn has an effect on the delay-time model results. A means of developing a detailed and comprehensive method of establishing failure rate was therefore required. The failure of a component or equipment generally has several influencing factors which contribute to failure. A modelling technique capable of taking into consideration these influencing factors is that of Bayesian network modelling. Chapter 5 re-examines the failure rate parameter, exploring the differing influencing factors responsible for the failure of a filter bag. The influencing factors are then modelled using Bayesian network modelling in order to establish the failure rate parameter. The integration of both the fuzzy set model and the Bayesian network model is illustrated in figure 6.1.

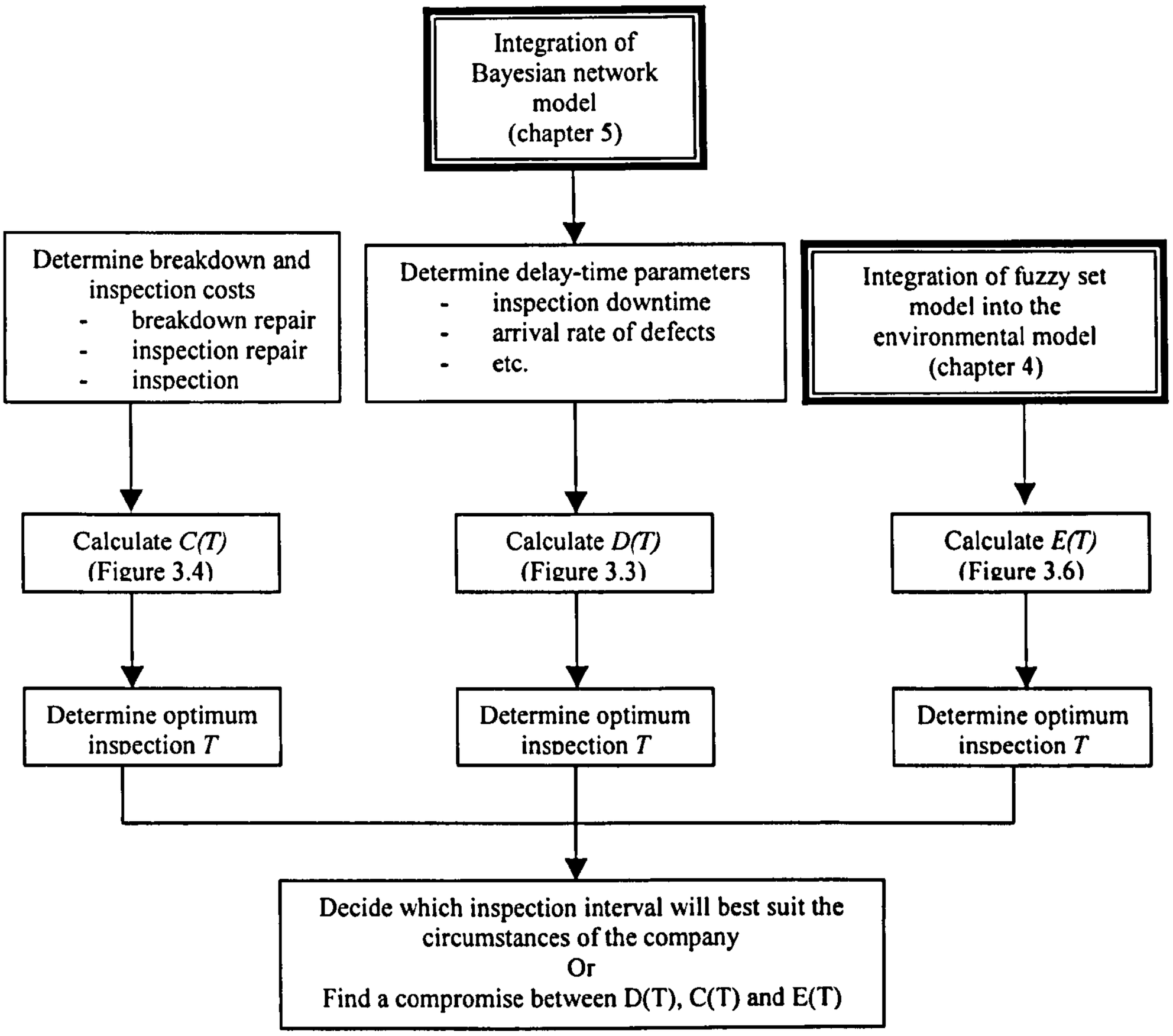


Figure 6.1. A flowchart illustrating the integration of fuzzy set modelling and Bayesian network modelling into the delay-time analysis methodology.

6.3 The introduction of Fuzzy set modelling into the environmental model, E(T)

The use of fuzzy logic to establish the environmental model allowed the use of linguistic terms from expert judgement to define the risk in terms of both the cost consequence as well as the probability of each parameter. The parameters take into account the risk to humans, both employees and the general public, ranging from injury to loss of life; the risk of collateral damage to industrial building as

well as residential building; lastly, the risk to the environment, both a direct cost as well as a clean-up cost. The parameters were originally established using expert judgement by means of a simple estimation of each.

The inclusion of fuzzy logic to generate the environmental parameters not only established accuracy and consistency for each parameter but also brings about a greater confidence in the overall results and conclusions of the study. It is important to point out that the same experts' used for the establishing of the original environmental modelling parameters were used for the fuzzy logic modelling of the environmental parameters. This resulted in a greater confidence of the results as it ensured consistency throughout the study.

The first parameter that was estimated was that of E_{health}. The original figure for this parameter was £5,000, the subsequent analysis utilising fuzzy logic as a modelling tool gave a figure for this parameter of £83,800. The next parameter to be scrutinised was that of $E_{collateral}$. The original figure for this parameter was estimated at £375,000 where as the fuzzy logic generated figure was £133,000. This particular result gave confidence that the fuzzy logic model was not simply over exaggerating each parameter, but instead giving a true value based on the judgement of the experts. The environmental parameter E_{damage} had an original estimate of £200,000, the fuzzy logic estimate being £445,000. The parameter $E_{reverse}$ was originally estimated at £250,000, the fuzzy logic estimation was that of £556,250. Finally the parameter E_{impact} was originally estimated £630,000, the fuzzy logic estimation gives a figure of £733,050. The original values for these parameters had been generally underestimated. This underestimation resulted in a distortion of the results for the delay-time environmental model. The delay-time model originally provided an inspection interval of 11 days with a cost of £27,624. The updated environmental model utilising fuzzy logic demonstrates an increase in the inspection interval to that of 13 days with a cost of £50,406. This increase in cost suggests that a greater level of detail was required when using

fuzzy logic modelling, compared to the original methods adopted, in order to carry out the estimation of each parameter.

6.4 Improvement to the parameter failure rate λ

The introduction of Bayesian network modelling to model the parameter failure rate λ was examined in chapter 5. Bayesian network modelling brought about a valuable insight as well as a greater level of understanding of the influencing factors responsible for the failure of a filter bag. After a rigorous and in-depth assessment of the failure of a filter bag using historical data and expert judgement, it was agreed that there were 4 possible influencing factors which contributed to failure. The influencing factors being; 'operating temperature', 'age of filter bag', 'competence of operator' and 'equipment failure'. An assessment was carried out for each influencing factor to establish their impact relating to the failure of a filter bag. This exercise also served to establish the dependencies of each influencing factor to one another. Prior probabilities were then established for each influencing factor, with careful consideration given to each probability. One criticism of Bayesian network modelling is the development of prior probabilities. Often data will be available in a variety of formats which makes transferring this information into a probabilistic model challenging. This transformation of data into failure probabilities was achieved through establishing a worst marginal frequency criterion. This simple equation (section 5.3.3, equation (5.1)) converted failure rates/frequencies into failure probabilities. The Bayesian model was then propagated in order to find the failure probability of a filter bag. The failure probability was then converted back to failure rate λ using the same equation. Originally the MTBF was calculated at 1095 days. The use of Bayesian network modelling recalculated this parameter to that of 476 days. This change in the failure rate was entered into the delay-time model and a direct comparison was then made. The inspection interval based on downtime D(T) changed from 11 days to 7 days. This marks a significant jump in the inspection

interval by simply re-evaluating one parameter in the delay-time analysis model, namely failure rate.

6.5 Overall improvement of Delay-time analysis from the integration of the models

In order to assess the benefits of integrating the fuzzy logic model and the Bayesian network model into the delay-time analysis models, a direct comparison is required between the original delay-time models and the improved delay-time models. Examining each delay-time model individually will highlight the changes that have taken place. A comparison of the downtime model D(T) shows a clear distinction between the originally developed delay-time model and the integrated delay-time model. The original model has a minimum inspection interval of 11 days whereas the improved model has significantly reduced the minimum inspection interval to that of 7 days. This comparison is illustrated in figure 5.11. The delay-time model relating to inspection costs C(T) also demonstrates a significant difference between the original delay-time model and the improved delay-time model. The original delay-time model calculated a minimum inspection interval, when costs are of primary concern, to that of 11 days. This figure moves to 7 days after incorporating the improved fuzzy logic and Bayesian network model parameters. This comparison is illustrated in figure 6.2.

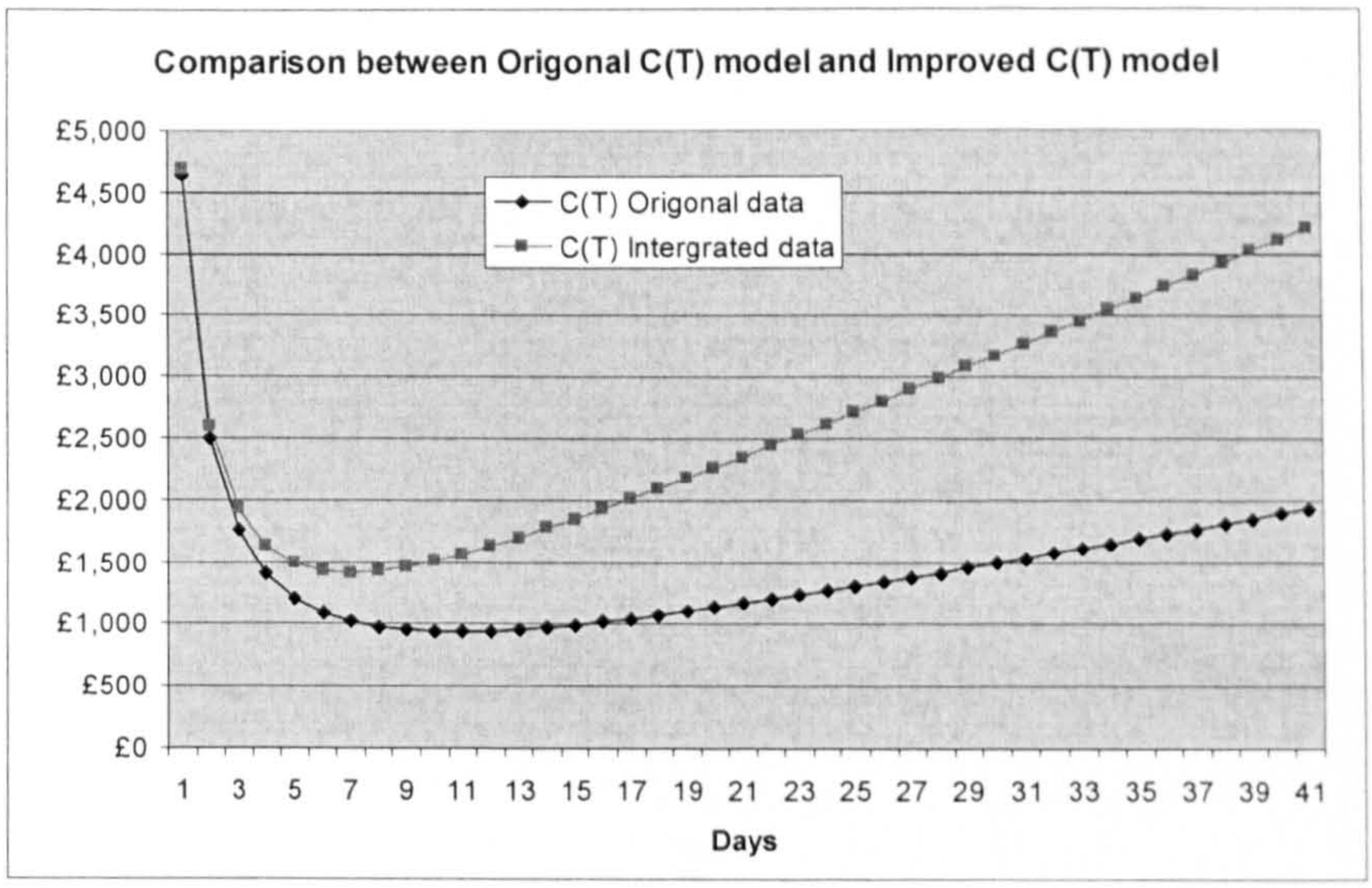


Figure 6.2. Comparison between the original delay-time model and the improved delay-time model for C(T).

Finally, a comparison of the original delay-time model relating to the environmental model E(T) and the improved delay-time model demonstrates less of a change compared to the D(T) model and the C(T) model. The inspection interval shows an increase from 11 days to 13 days. The difference in the expected cost however almost doubled from the original model to the improved model. A comparison of the original delay-time model and the improved delay-time model for the environmental model E(T) is illustrated in figure 6.3.

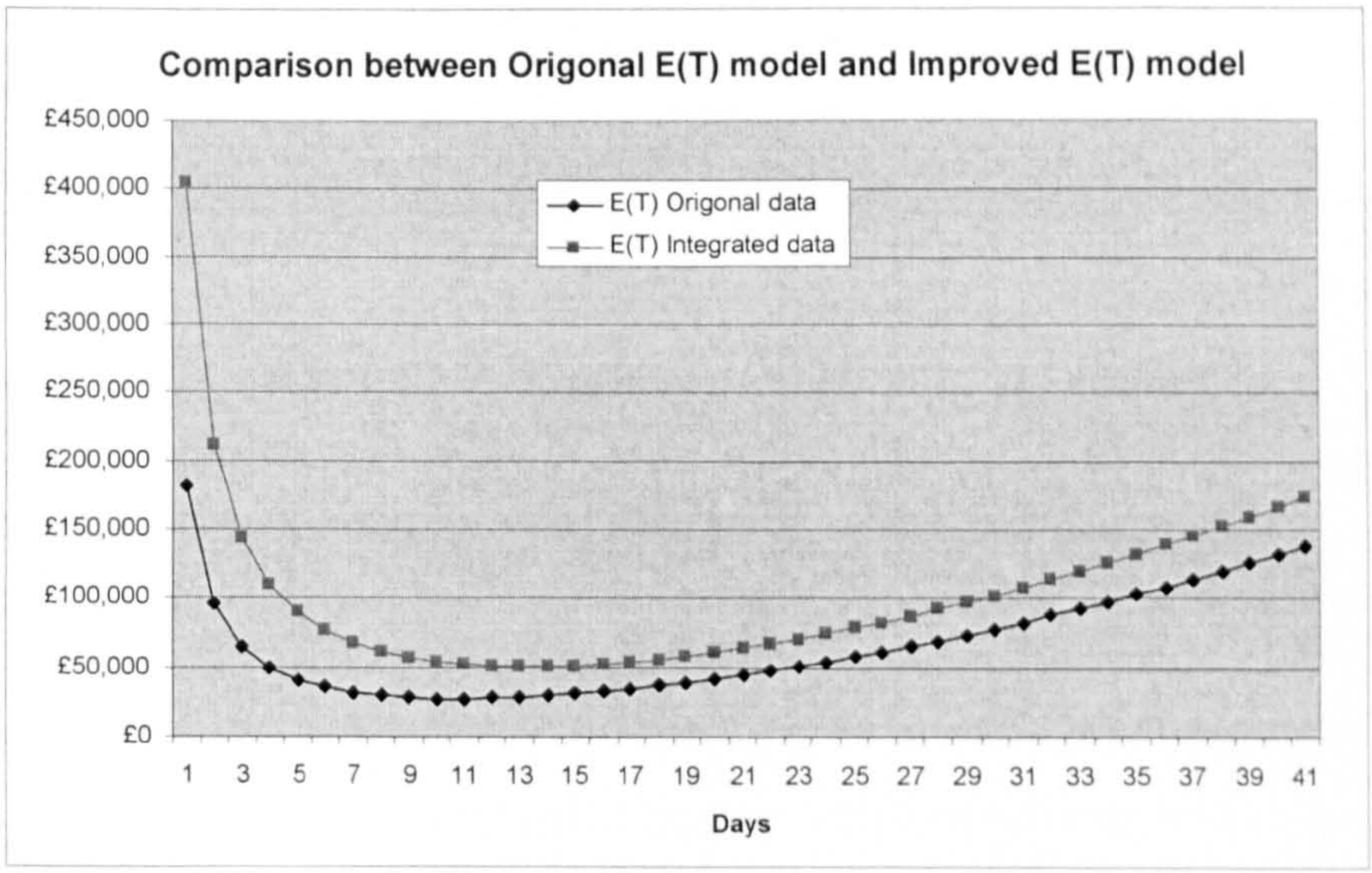


Figure 6.3. Comparison between the original delay-time model and the improved delay-time model for E(T).

6.6 Conclusion

There are several important conclusions which may be drawn from the introduction of the improved parameters to the delay-time models. The modelling of the environmental model E(T) using fuzzy logic introduced a greater level of detail than was previously considered. Originally the environmental parameters were established through the use of expert judgement, with care taken to ensure consistency between each result with careful consideration given to each experts perception of each parameter. The introduction of fuzzy logic to model the required parameters still relied on subjective judgement, but the process of establishing each parameter not only ensured a greater consistency but also succeeded in developing an extensive in-depth assessment of each parameter.

The use of Bayesian network modelling to establish an improvement to the parameter failure rate λ (1/MTBF) advanced the overall delay-time analysis

model further. The original assessment of failure rate was established through two pieces of information, namely: how many failures have occurred? over what period of time has these failures taken place?. Although generally used and accepted this fails to take other influencing parameters into account. The use of Bayesian network modelling was capable of modelling the influencing parameters responsible for failure and establishing an improved figure for failure rate λ (i.e. 1/MTBF). The use of Bayesian network modelling may be utilised in other parameters relating to delay-time analysis in order to bring about further improvements. The parameter 'downtime due to inspection' could be examined further to understand the influencing factors which contribute to this parameter. Analysis in this area may uncover aspects such as poor inspection procedures or inadequate training of inspection personnel. This may be applied equally to the parameter 'arrival rate of defects' whereby the influencing factors may be considered through rigorous analysis. Analysis might find poor maintenance repairs, inadequate training of maintenance staff or use of inferior components used for repair. Finally, the delay-time parameter 'average downtime for breakdown repair' may be considered for analysis using Bayesian network modelling. This parameter may have greater importance due to its potential to stop production. The analysis of this parameter could bring about a greater impact to productivity and costs through an improved understanding of the influencing parameters responsible.

The combining of the two modelling techniques, fuzzy logic modelling and Bayesian network modelling, into the delay-time analysis model for D(T), C(T) and E(T) has shown an increase in understanding of the parameters. This understanding has revealed details which could have gone unnoticed using the original data.

Chapter 7

Conclusion

Summary

This chapter will summarise the main conclusions drawn from this study, highlighting the specific contribution which has been achieved to this field of research. This chapter will also discuss the limitations of the research which were encountered and in doing so outline future possible research which could be conducted.

7.1 Introduction

A detailed review of manufacturing practices and maintenance concepts was carried out (chapter 2) in order to gain an insight and understanding of the current situation that exists in the manufacturing industry today. It was discovered that although there are a multitude of different manufacturing processes employed throughout industry, there is an equally diverse variety of maintenance strategies utilised in order to ensure successful productivity. This thesis draws attention towards the problems relating to establishing optimal inspection intervals in the manufacturing industry, in doing so demonstrates a possible solution utilising a risk-based maintenance methodology.

7.2 Main conclusions

The use of delay-time analysis to establish optimal inspection intervals for a company producing carbon black has been the main area of this research. The

technique combined the use of probabilistic data together with objective and subjective data. The inspection intervals established enable engineers and managers to set inspection regimes based on both qualitative and quantitative information.

A main aim of this research was to produce a maintenance methodology for a manufacturing industry using risk-based analysis in order to establish a suitable inspection interval. This thesis has employed a number of analytical techniques in order to achieve this aim. The use of delay-time analysis in this study has demonstrated that an advanced method of maintenance modelling can be used in a medium sized manufacturing / process company.

The use of delay-time analysis to establish efficient maintenance regimes through the minimising of downtime D(T) and costs C(T) enables managers to make informed decisions based either on reducing downtime or reducing costs or both. The introduction of the environmental model E(T) has introduced another facet to consider when developing a maintenance strategy. The environmental model, applied to an industry producing potentially damaging environmental products or substances, has considered the risks associated with the failure of a component or equipment on the environment. The model can not only be applied to an industry producing hazardous materials but could equally be applied to the transportation of hazardous goods.

7.3 Research contribution

The methodology of applying delay-time analysis to an industry producing hazardous and environmentally sensitive products has been developed. The delay-time analysis established optimal inspection intervals through minimising downtime D(T) and costs relating to maintenance and inspection C(T). In addition to the downtime model and cost model, an environmental model E(T) was also

developed. The environmental model took into consideration factors relating to humans, factors relating to collateral damage and factors relating to the cost to the environment. Through the use of fuzzy set modelling the environmental model was refined and enhanced which resulted in a greater depth of understanding and confidence in the model. Additionally, the use of Bayesian network modelling further developed and enhanced the parameter failure rate λ, which is a key ingredient in all three delay-time models D(T), C(T) and E(T). The overall effect of the delay-time analysis with the integration of fuzzy set theory and Bayesian network modelling gives a robust and assured method of establishing maintenance and inspection regimes.

7.4 Limitations

When applying delay-time analysis to any problem it is vital to appreciate what exactly the results are illustrating. The use in this study of delay-time analysis always illustrates a worst-case scenario. This worst-case scenario condition is that if a failure does not take place before inspection then it will take place during inspection repair. Conversely, a best-case scenario is that no breakdown failures would occur and no failure repairs will take place at inspection.

The failure distribution that was used in the delay-time model was exponential distribution. This distribution, however, only deals when the failure of a component or equipment is said to have a constant rate of failure. This may limit the application of delay-time analysis to certain types of equipment or components.

The methodology demonstrated in this thesis has been successfully applied to a company producing carbon black. In order to gain a greater confidence and

insight into the uses and limitations of this methodology it will need to be applied to several industries from differing sectors.

7.5 Future research

Having established the difference between best case scenario and worst case scenario a possible area of research could be establishing a compromise between each case and setting inspection intervals based on both scenarios.

Another area of research which could be explored is including differing failure distributions into the delay-time model. For this research the exponential distribution was used for its suitability to the type of failures which were encountered. Research could focus on applying delay-time analysis to an industry that possesses equipment which exhibit a different failure distribution than that of exponential, for example, the normal distribution function is widely used for modelling repair activities. Other failure distributions which could be considered include weibull, beta, gamma and lognormal. Assessment of their suitability to the data available could be carried out with the most suitable distribution, or a combination of distributions, being selected.

Finally, a fundamental part of the delay-time analysis process is establishing the probability of a defect leading to a breakdown, this is given the term *b(T)*. The introduction of Monte Carlo simulation into the delay-time analysis in order to establish b(T) could serve to numerically produce the probabilities which are needed. There may well be a limitation to this method as there is reliance on the input data being of a uniform distribution, plus the amount of samples must be reasonably high in order to ensure accuracy of the simulation.

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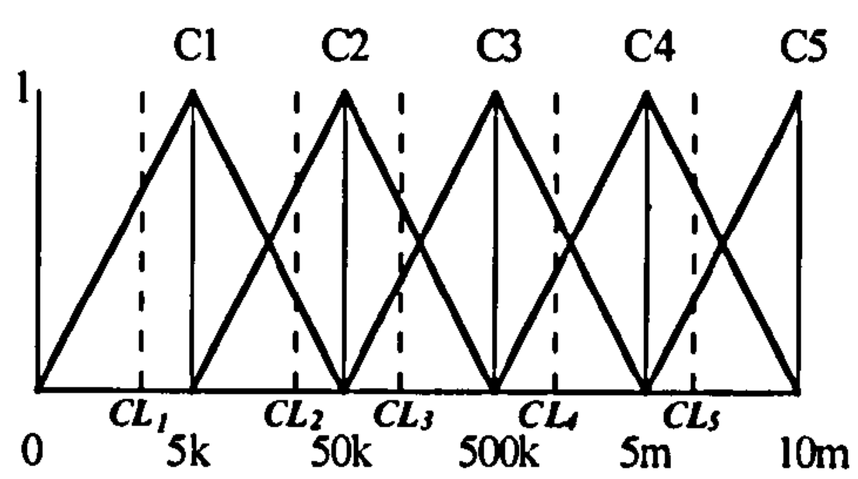
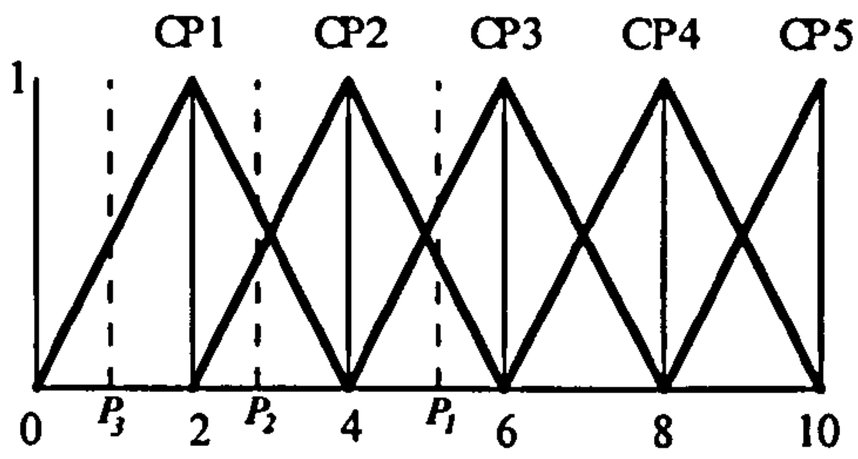
Appendices

Appendix 1 – Fuzzy logic results for expert 2 and expert 3

Expert #2 results for E_{health}





Membership function of consequence for E_{health}

CL_1	(C1 = 0.68) (C2 = 0) (C3 = 0) (C4 = 0) (C5 = 0)
CL_2	(C1 = 0.30) (C2 = 0.70) (C3 = 0) (C4 = 0) (C5 = 0)
CL_3	(C1 = 0) (C2 = 0.61) (C3 = 0.39) (C4 = 0) (C5 = 0)
CL_4	(C1 = 0) (C2 = 0) (C3 = 0.60) (C4 = 0.40) (C5 = 0)
CL_5	(C1 = 0) (C2 = 0) (C3 = 0) (C4 = 0.68) (C5 = 0.32)

Membership function of conditional probability for E_{health}

P_1	(CP1 = 0) (CP2 = 0.44) (CP3 = 0.56) (CP4 = 0) (CP5 = 0)
P_2	(CP1 = 0.59) (CP2 = 0.41) (CP3 = 0) (CP4 = 0) (CP5 = 0)
P_3	(CP1 = 0.46) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

P_4 (CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

P_5 (CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

Cost consequence, CL_n and a conditional probability P_n

CL_1; probability P_1

C1 (0.68) and CP2 (0.44)	EC1 0.44, EC2 0.20	Rule 6 fired
C1 (0.67) and CP3 (0.56)	EC2 0.56	Rule 11 fired

CL_2; probability P_2

C1 (0.30) and CP1 (0.59)	EC1 0.30	Rule 1 fired
C1 (0.28) and CP2 (0.41)	EC1 0.28, EC2 0.20	Rule 6 fired
C2 (0.70) and CP1 (0.59)	EC1 0.59, EC2 0.20	Rule 2 fired
C2 (0.70) and CP2 (0.41)	EC2 0.41	Rule 7 fired

CL_3; probability P_3

C2 (0.61) and CP1 (0.46)	EC1 0.46, EC2 0.20	Rule 2 fired
C3 (0.39) and CP1 (0.46)	EC2 0.39	Rule 3 fired

Synthesising:

CL_1; probability P_2	EC1 0.44; EC2 0.56
CL_2; probability P_1	EC1 0.59; EC2 0.41
CL_3; probability P_3	EC1 0.46; EC2 0.39

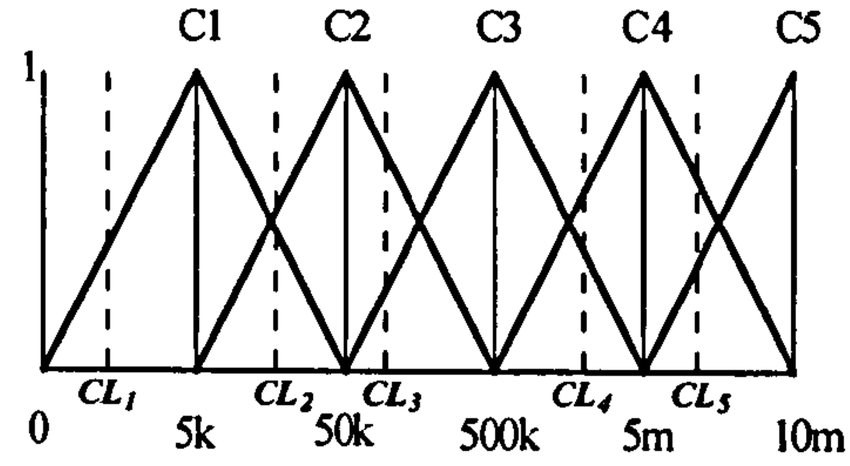
Normalising:

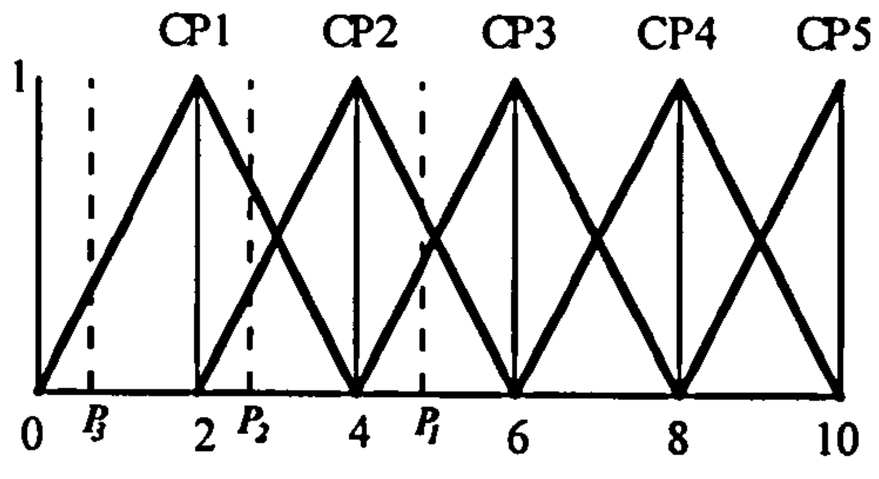
CL_1; probability P_2	EC1 0.44; EC2 0.56

CL_2; probability P_1 EC1 0.59; EC2 0.41

CL_3; probability P_3 EC1 0.54; EC2 0.46

Expert #3 results for E_{health}





Membership function of consequence for E_{health}

CL_1 (C1 = 0.42) (C2 = 0) (C3 = 0) (C4 = 0) (C5 = 0)

CL_2 (C1 = 0.45) (C2 = 0.55) (C3 = 0) (C4 = 0) (C5 = 0)

CL_3 (C1 = 0) (C2 = 0.73) (C3 = 0.27) (C4 = 0) (C5 = 0)

CL_4 (C1 = 0) (C2 = 0) (C3 = 0.41) (C4 = 0.59) (C5 = 0)

CL_5 (C1 = 0) (C2 = 0) (C3 = 0) (C4 = 0.64) (C5 = 0.36)

Membership function of conditional probability for E_{health}

P_1 (CP1 = 0) (CP2 = 0.59) (CP3 = 0.41) (CP4 = 0) (CP5 = 0)

P_2 (CP1 = 0.67) (CP2 = 0.33) (CP3 = 0) (CP4 = 0) (CP5 = 0)

P_3 (CP1 = 0.32) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

P_4 (CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

P_5 (CP1 = 0) (CP2 = 0) (CP3 = 0) (CP4 = 0) (CP5 = 0)

Cost consequence, CL_n and a conditional probability P_n

CL_1; probability P_1

C1 (0.42) and CP2 (0.59)	EC1 0.42, EC2 0.20	Rule 6 fired
C1 (0.42) and CP3 (0.41)	EC2 0.41	Rule 11 fired

CL_2; probability P_2

C1 (0.45) and CP1 (0.67)	EC1 0.45	Rule 1 fired
C1 (0.45) and CP2 (0.33)	EC1 0.33, EC2 0.20	Rule 6 fired
C2 (0.55) and CP1 (0.67)	EC1 0.55, EC2 0.20	Rule 2 fired
C2 (0.55) and CP2 (0.33)	EC2 0.33	Rule 7 fired

CL_3; probability P_3

C2 (0.73) and CP1 (0.32)	EC1 0.32, EC2 0.20	Rule 2 fired
C3 (0.27) and CP1 (0.32)	EC2 0.27	Rule 3 fired

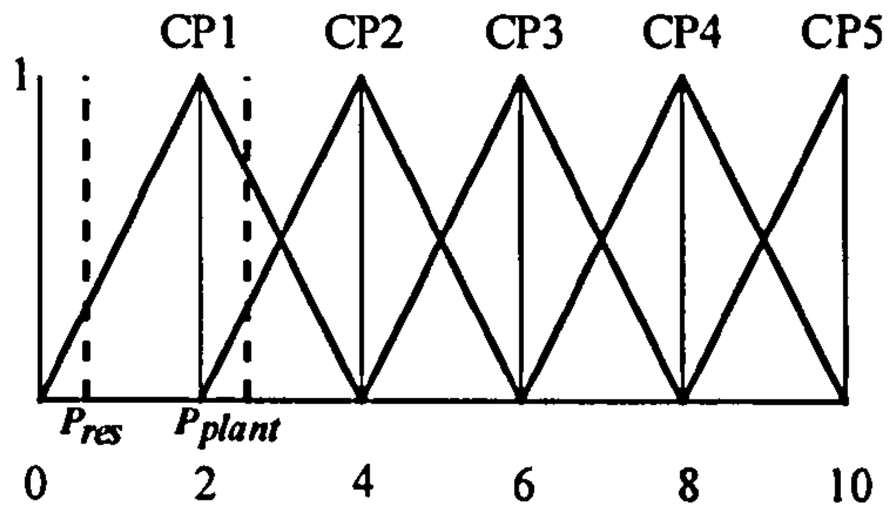
Synthesising:

CL_1; probability P_3	EC1 0.42; EC2 0.41
CL_2; probability P_2	EC1 0.55; EC2 0.33
CL_3; probability P_3	EC1 0.32; EC2 0.27

Normalising:

CL_1; probability P_3	EC1 0.51; EC2 0.49
CL_2; probability P_2	EC1 0.63; EC2 0.37
CL_3; probability P_3	EC1 0.54; EC2 0.46

Expert #2 results for $E_{collateral}$



$Cost_{plant}$; probability P_{plant}

C3 (0.45) and CP1 (0.73)	EC2 0.45	Rule 3 fired
C3 (0.45) and CP2 (0.27)	EC2 0.27, EC3 0.20	Rule 8 fired
C4 (0.55) and CP1 (0.73)	EC2 0.55, EC3 0.20	Rule 4 fired
C4 (0.55) and CP2 (0.27)	EC3 0.27	Rule 9 fired

$Cost_{res}$; probability P_{res}

C2 (0.73) and CP1 (0.28)	EC1 0.28, EC2 0.20	Rule 2 fired
C3 (0.27) and CP1 (0.28)	EC2 0.27	Rule 3 fired

Synthesising:

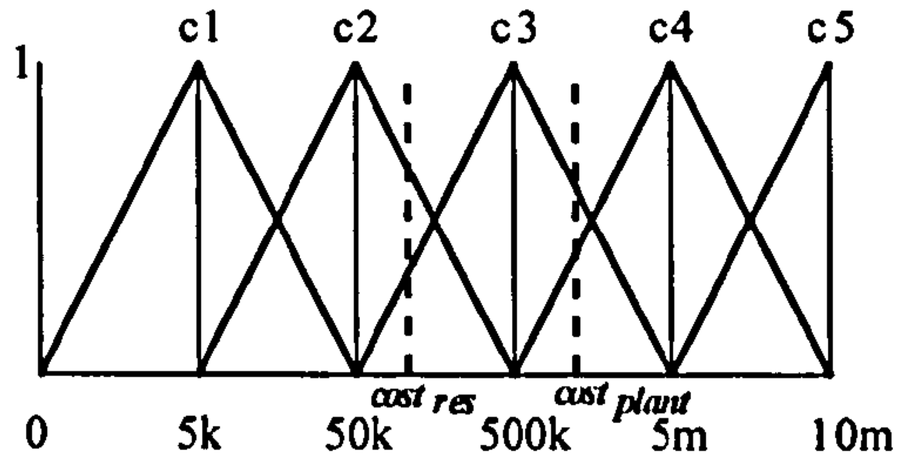
$Cost_{plant}$; probability P_{plant}	EC2 0.55; EC3 0.27
$Cost_{res}$; probability P_{res}	EC1 0.28; EC2 0.27

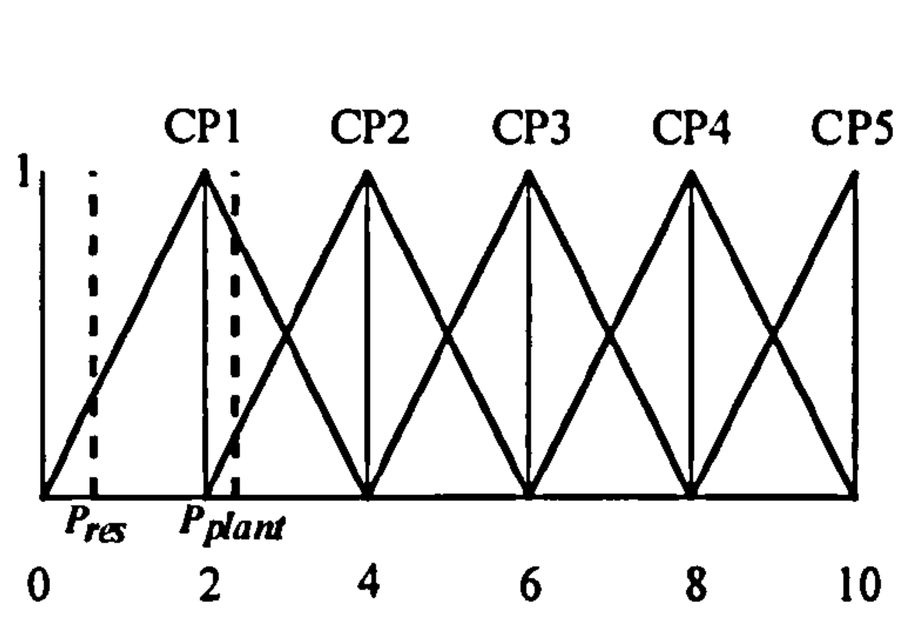
Normalising:

$Cost_{plant}$; probability P_{plant}	EC2 0.67; EC3 0.33
$Cost_{res}$; probability P_{res}	EC1 0.51; EC2 0.49

$Cost_{plant}$; probability P_{plant}	(£50,000 x 0.67) + (£250,000 x 0.33 = £116,000
$Cost_{res}$; probability P_{res}	(£10,000 x 0.51) + (£50,000 x 0.49) = £29,600

Expert #3 results for $E_{collateral}$





$Cost_{plant}$; probability P_{plant}

C3 (0.61) and CP1 (0.81)	EC2 0.61	Rule 3 fired
C3 (0.61) and CP2 (0.19)	EC2 0.19, EC3 0.19	Rule 8 fired
C4 (0.39) and CP1 (0.81)	EC2 0.39, EC3 0.20	Rule 4 fired
C4 (0.39) and CP2 (0.19)	EC3 0.19	Rule 9 fired

$Cost_{res}$; probability P_{res}

C2 (0.67) and CP1 (0.32)	EC1 0.32, EC2 0.20	Rule 2 fired
C3 (0.33) and CP1 (0.32)	EC2 0.32	Rule 3 fired

Synthesising:

$Cost_{plant}$; probability P_{plant}	EC2 0.61; EC3 0.20
$Cost_{res}$; probability P_{res}	EC1 0.32; EC2 0.32

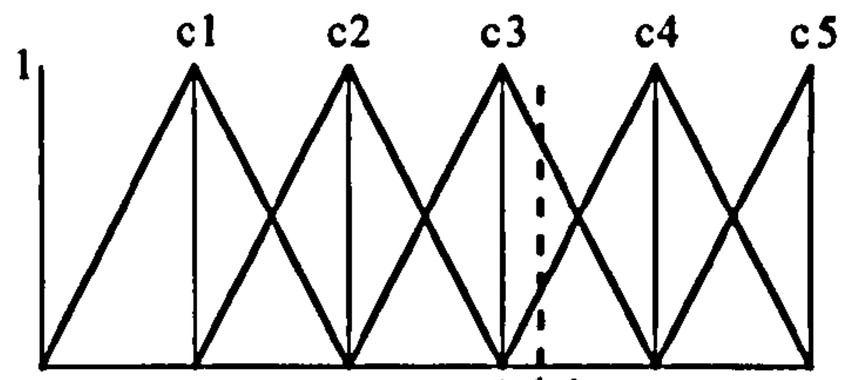
Normalising:

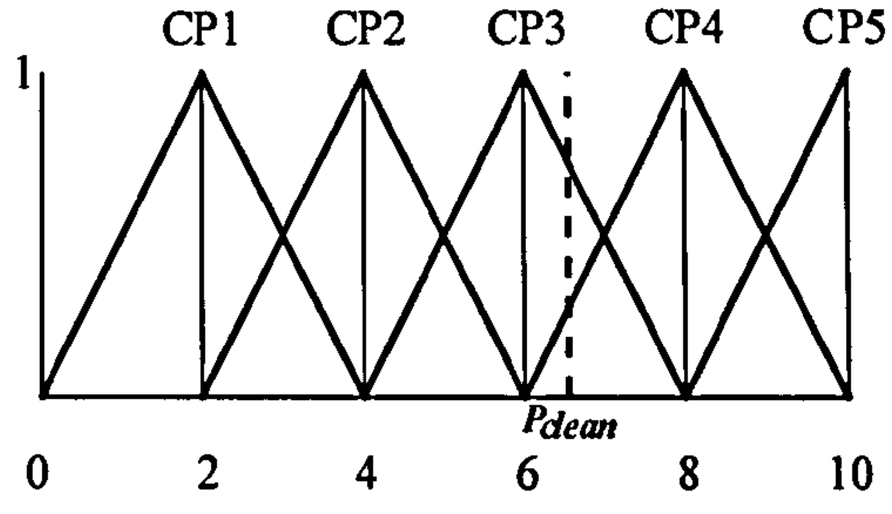
$Cost_{plant}$; probability P_{plant}	EC2 0.75; EC3 0.25
$Cost_{res}$; probability P_{res}	EC1 0.50; EC2 0.50

Expert #3 result:

$Cost_{plant}$; probability P_{plant}	(£50,000 x 0.75) + (£250,000 x 0.25)= £100,000
$Cost_{res}$; probability P_{res}	(£10,000 x 0.50) + (£50,000 x 0.50) = £30,000

Expert #2 results for E_{damage}





$Cost_{clean}$; probability P_{clean}

C3 (0.74) and CP3 (0.73)	EC3 0.73	Rule 13 fired
C3 (0.74) and CP4 (0.27)	EC3 0.27, EC4 0.20	Rule 18 fired
C4 (0.26) and CP3 (0.73)	EC3 0.26, EC4 0.20	Rule 14 fired
C4 (0.26) and CP4 (0.27)	EC4 0.26	Rule 19 fired

Synthesising:

$Cost_{clean}$; probability P_{clean} EC3 0.73; EC4 0.26

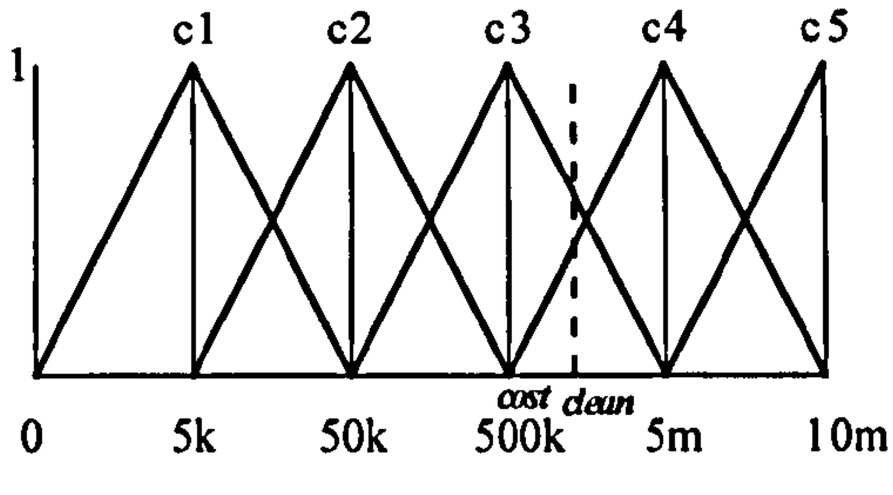
Normalising:

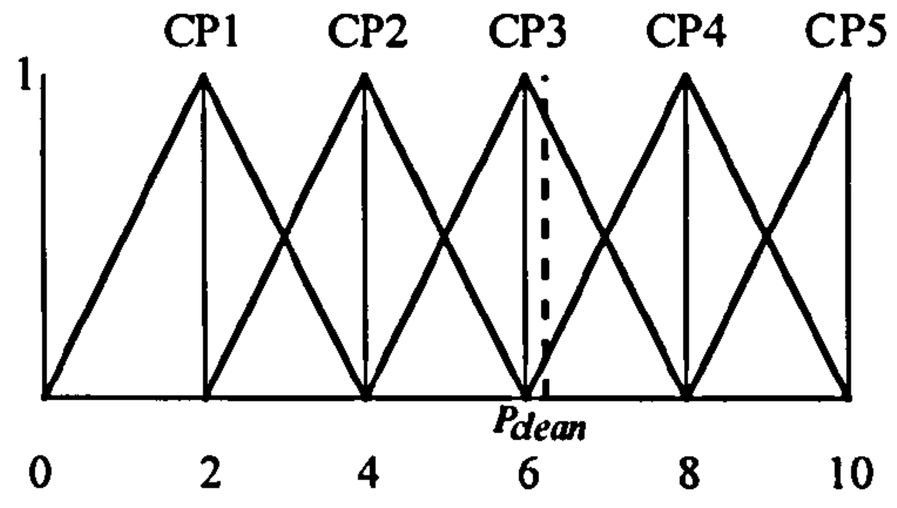
$Cost_{clean}$; probability P_{clean} EC3 0.74; EC4 0.26

Expert #2 result:

$Cost_{clean}$; probability P_{clean} (£250,000 x 0.74) + (£1m x 0.26) = £445,000

Expert #3 results for E_{damage}





$Cost_{clean}$; probability P_{clean}

C3 (0.58) and CP3 (0.88)	EC3 0.58	Rule 13 fired
C3 (0.58) and CP4 (0.12)	EC3 0.12, EC4 0.12	Rule 18 fired
C4 (0.42) and CP3 (0.88)	EC3 0.42, EC4 0.20	Rule 14 fired
C4 (0.42) and CP4 (0.12)	EC4 0.12	Rule 19 fired

Synthesising:

$Cost_{clean}$; probability P_{clean}	EC3 0.58; EC4 0.20

Normalising:

$Cost_{clean}$; probability P_{clean}	EC3 0.74; EC4 0.26

Expert #3 result:

$Cost_{clean}$; probability P_{clean} (£250,000 x 0.74) + (£1m x 0.26) = £445,000

Appendix 2 – Papers published during the course of the research

Papers published:

'Delay-Time Concept and its Application to Maintenance Problems'. Journal of Safety & Reliability Society. Vol.27. No. 2. pp 5-19.

Abstract: *This paper has been written to give a brief view of inspection maintenance policies and the concept of delay-time analysis as a tool to achieve cost effective inspection maintenance and to reduce breakdown times. The paper also looks at future possible applications for this, developing a delay-time for individual parts or pieces of equipment and combining them to establish delay-time analysis for a group of parts or equipment. Also, the paper highlights the need to document failure data and maintenance data in a standard format to help develop delay-time as a tool in order to help smaller companies take advantage of this modelling concept.*

'Methodology for using delay-time analysis for a manufacturing industry'. Journal of Reliability Engineering and System Safety. Vol.94. pp 111-124.

Abstract: *This paper has been written to give a methodology of applying delay-time analysis to a maintenance and inspection department. The aim is to reduce downtime of plant items and/or reducing maintenance and inspection costs, taking into account the possible environmental impact of a failure in terms of cost, both to the company and the environment. The paper also attempts to give a subjective measure of the consequences of such a failure in terms of cost to the environment, in monetary value to the company and the damaging effect to the company image.*

Papers awaiting publication:

'The gathering and use of data using fuzzy set theory for applying delay-time analysis to a manufacturing industry'; submitted to IMechE, Part E, Journal of Process Mechanical Engineering.

Abstract: *This paper has been written to give a standardisation of information for applying delay-time analysis to a maintenance and inspection department. The aim of this paper is to take both subjective and objective information gathered and elicit the required information using fuzzy set modelling for the purpose of applying it to delay-time analysis. A methodology has been developed and applied to a case study in order to demonstrate the process involved.*

'The use of Bayesian network modelling for maintenance planning in a manufacturing industry'.

Abstract: *This paper has been written in order to apply Bayesian network modelling to a maintenance and inspection department. The primary aim of this paper is to establish and model the various parameters responsible for the failure rate of a system, using Bayesian network modelling, in order to apply it to a delay-time analysis study. The use of Bayesian network modelling allows certain influencing events to be considered which can affect parameters relating to the failure rate of a system. Bayesian network modelling also allows these influencing events to change and update depending on the influencing data available at any given time, thus changing the failure rate or probability of failure. A methodology has been developed and applied to a case study in order to demonstrate the process involved.*

Conference papers:

'Delay-Time Concept and its Application to Maintenance Problems'. The 6th IMA (Institute of Mathematics and its Applications) International Conference. September 2007, The Lowry Centre, Salford Quays, Manchester. United Kingdom.

'Methodology for using delay-time analysis for a manufacturing industry'. The International Conference on Manufacturing Research. September 2008. Brunel University, London. United Kingdom.

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Appendix 3 – Sample of maintenance and inspection data for 3 months for units A, C and D

Date	Unit	Down Time (Hours)	Shift	SM	Down Time Reason	Action Updated From SMs meeting UNTIL 21st Feb
03-Apr-06	A	4.63	A	AH	MUF No 6 air trap bearing failure.	New PM's in place to carry out bearing changes 12 months. QA required for stores stock items that have been repaired or new.
20-Apr-06	A	2.37	D	AW	K+ pump failure. Replacement pump took fuse out	K+ Pump Trial new (Smaller Head) pump with S/S balls. Up-Grade workshop test rig, to include pulsation damper, needle valve & 4-20 mA injection. (mimic CRA conditions). Write QA control for K+ pumps in stores. To include witness, prove & label.
28-Apr-06	A	25.81	D	AW	No 9 Sub Station HT Failure	RCA - K+ Tank drain pipe fractured in cable trench. Training session with high volume of dumping K+ mix. Hot water in trench, condensation in sub station. Q Breaker tripped when water entered protection device.
06-May-06	A	8.90	C	GMc	No 2 Air Compressor failure. Lack of H.P Air	No2 Compressor failure. Lack of H.P Air. From log: - Atlas contacted and came out to No2 compressor. Fault traced to the oil pump. The drive shaft had sheared. Took oil pump off site for a rebuild. Returned and fitted. Compressor back on line @ 1400hrs.Unable to contact Hewdwen air for a Mobile compressor. All emergency No's are not valid. (need updating). Action Up date emergency telephone numbers GS. GEW to discuss failure with Atlas. Is service interval correct?
12-May-06	A	0.88	E	DJ	N Blower Electrical Failure.	N Blower Failure. Motor down to earth. Tripped on overload. Removed off site. Back on site Monday 15th. Report to follow. RCA required. Action GEW/JA
19-May-06	A	31.25	C	GMc	MUF Bag leakage, Down for MUF bag check	Planned downtime. MUF bag leak. 1 off bag with failed ring plus 1 off cell plate blanking ring leaking. Signs of acid condensation. Poor turnaround time. Maintenance finshied 14:00.

20-May-06	A	0.17	E	DJ	MUF High Filter Pressure (Delta P). Human error - air supply off to muf poppets	Failure of following start up procedures.
20-May-06	A	1.33	E	DJ	Reactor, unable to remove blocked transition jet	Transition doubled transitioned tip!
23-Jun-06	A	1.67	B	LD	Free water in reactor	Could not raise iodine number. Grade change from Hybrid trial from one quench stick operation to two. High water flow on one stick causing loss of water pattern. Free water found in reactor. Re-examine grade change procedures. GS
26-Jun-06	A	24.15	C	GMc	Main Unit Filter, Shutdown for MUF bag check	Bag Check - Dirty cloth. Large number of bags showing signs of ring failure.
28-Jun-06	A	11.72	C	GMc	Main Unit Filter, Shutdown for MUF bag check	e-Check - Dirty cloth check after going on load. Cell plate holed. (Corrosion from acid rain)
30-Jun-06	A	1.98	A	AW	Rotating Equipment Failure, Raw Materials Handling Tank 7 transfer pump failed.	Tank 7 Transfer pump failure. Tripping Unit A & Unit.

12-Apr-06	C	10.18	A	AH	Repair leaking feedstock pump	Ryland pump leaking. Changed out with stores spare. Stores spare in poor condition. Action QA required for all equipment repaired off site.
13-Apr-06	C	16.75	E	AW	Pumps, Ryland pump leaking.	As above.
07-May-06	C	19.75	B	LD	Drier Drive motor & Gear box bed plate bolts sheared.	Work carried out to re-bolt down motor & gearbox. Further work required in Unit shutdown. RCA required. Action GEW/JA
10-May-06	C	0.77	E	DJ	Proximity failure on vent damper (FV205R1	Proximity switch changed out. No signs of mechanical failure or damage.
12-May-06	C	8.75	E	DJ	N Blower Electrical Failure.	As Unit A
19-May-06	C	3.40	A	AW	Flame failure, no fault found, relay swopped for HTF relay.	No fault found. Reactor left on MBHL for several hours ,no issues. Flame eye, relay & amplifier checked on next downtime, again no issues found.
26-May-06	C	4.18	C	GMc	Fouled Heat Exchanger,	Offload for defoul - Planned.

02-Jun-06	C	0.18	B	TS	Low Combustion Air	N Blower Trip (Plus other drives) Manweb power dip. Manweb contacted. A Customer had caused spike. Dip not long enough for G59 to operate. Only Unit C failed. Motor tested as if fault as a precaution.

03-Apr-06	D	0.25	B	LD	Reactor, unable to get gas onto atomised stinger/ wrong grade load	IT Issue.
28-Apr-06	D	25.81	D	AW	No 9 Sub Station HT Failure	See Unit A
12-May-06	D	11.55	E	DJ	N Blower Electrical Failure.	As Unit A
19-May-06	D	0.15	C	GMc	Quench Operation, Trip due to loss of RO water pressure shutting down unit A	Unit tripped to MBHL @ 0029hrs. Due to dip in RO water pressure. Unit to MBHL @ 0014hrs. Unit As soon as MBHL is selected primary quench still goes into forced manual @ 100%. This does not clear until unit has reached MBHL (10mins later). This robbed the RO water and the pressure dropped tripping both unit A and unit D to quench. We got no alarm on unit D for this. The first we new was when unit D tripped to MBHL. **ACTION - Unit A Quench Flow Tx requires re-ranging. GS**
30-Jun-06	D	3.55	A	AW	Rotating Equipment Failure, Raw Materials Handling Tank 7 transfer pump failed.	As Unit A