INTEGRATION OF HUMAN FACTORS INTO DELAY TIME MODEL USING FUZZY LOGIC

BY

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Dedicated to my family with love

This thesis is dedicated to my Idol, my beloved Father, Nesar Ammar Merah

To my Beautiful Mother, my Amazing Brothers and Sister

Thank you

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

THESIS ABSTRACT

Full Name : YOUCEF MERAH

Thesis Title : INTEGRATION OF HUMAN FACTORS INTO DELAY TIME MODEL USING FUZZY LOGIC

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In today's competitive environment, the importance of scheduling maintenance activities has increased. The substantial involvement of humans in maintenance activities makes the incorporation of human factors in maintenance activities essential. The involvement of human factors affects the maintenance activities on the objects and though affects the expected downtime of the objects concerned. The maintenance activities performed on the machines results in costs incurred at the system level. Delay time modelling is considered one of the maintenance activities that is commonly used in plants in order to prevent failures of machines and equipment. The main purpose of this thesis is to study the integration of the human factors into the delay time modelling to minimize the expected downtime and the expected total cost. Two models have been developed in this thesis. The first model integrates the delay time model and the human factors by including the human factors in the inspection time. The second model integrates the human factors and the delay time model by adding the human factors in the delay time and the

inspection time together. The two models are developed and tested with examples from the literature. The results of the first model show that the integrated model gives a lower expected total cost and a slightly higher expected downtime. The second model resulted in lower expected downtime and lower expected total cost. The results comparisons are compared to the results obtained from the original delay time model.

ملخص الرسالة

الاسم الكامل: يوسف ناصر مراح

عنوان الرسالة: دمج العوامل البشرية في نموذج وقت التأخير باستخدام المنطق الضبابي

التخصص: هندسة النظم الصناعية

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في بيئة تنافسية اليوم ، ازدادت أهمية جدولة أعمال الصيانة. المشاركة الكبيرة للبشر في أنشطة الصيانة تجعل دمج العوامل البشرية في أعمال الصيانة أمرًا ضروريًا. تؤثر مشاركة العوامل البشرية على أنشطة الصيانة على الآلات والمعدات ، وإن كانت تؤثر على وقت التوقف المتوقع الآلات والمعدات المعنية. تؤدي أنشطة الصيانة التي تتم على الآلات إلى التكاليف المتكبدة على مستوى النظام. يعتبر نمذجة تأخير الوقت أحد أنشطة الصيانة المستخدمة بشكل شائع في المصانع من أجل منع توقف الآلات والمعدات. الغرض الرئيسي من هذه الرسالة هو دراسة دمج العوامل البشرية في نمذجة وقت التأخير لتقليل وقت التوقف المتوقع والتكلفة الإجمالية المتوقعة. تم تطوير طرازين في هذه الرسالة. يدمج النموذج الأول وقت التأخير معالعوامل البشرية المؤثرة من خلال تضمين العوامل البشرية في وقت الفحص. النموذج الثاني يدمج العوامل البشرية مع نموذج التأخير الزمني بإضافة العوامل البشرية في وقت التأخير وزمن الفحص معا. تم تطوير واختبار النموذجين مع أمثلة من الأدبيات. تظهر نتائج النموذج الأول أن النموذج المتكامل يعطي تكلفة إجمالية متوقعة أقل ووقت تعطل متوقع أعلى قليلاً. أدى النموذج الثاني إلى انخفاض وقت التوقف المتوقع وانخفاض التكلفة الإجمالية المتوقعة. وقد تم عمل مقارنات للنتائج التي تم الحصول عليها من نموذج وقت التأخير الأصلي.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Maintenance involves all activities that are necessary to retain plant assets in functioning states. It is performed in parallel to production and can have a great effect on production capacity and product quality. Studies have found that maintenance constitutes the largest part of any operational budget after energy costs and may account for up to 40% of total production cost **Mobley (1990)**. Therefore, huge gain could be achieved by correctly planned and executed maintenance actions.

In this research delay time model will be modified to include the human factors (which is explained in section 1.3). This is due to the heavy involvement of humans in the maintenance activities. The human factors will be injected into the delay time model in two different aspects. The first will be for the inspection time and the second will be in modeling the delay time. This chapter includes an introduction of the thesis. The

introduction covers two main topics, maintenance and human factors. The maintenance section explains the common maintenance policies, the maintenance terms that will be used, preventive maintenance and the delay time model, and lastly cost reductions using the maintenance policies. The human factors section includes an introduction about the human factors and the common human factors terms that are used in the thesis. Following these two sections, the thesis objectives are listed and discussed. Lastly the organization of the thesis is illustrated, and the chapters are explained in detail.

1.2 Maintenance

Maintenance is performed on almost all systems that include machines, equipment, tools and materials. The interest in maintenance has grown so large after World War II and the research in implementing and improving maintenance techniques and policies is advancing. **Latino (1999)** mentioned that in the US industry over $300 billion is spent on maintenance and operations of plants. Almost $240 billion of this amount is spent on correcting the faults and failures of machines, systems and people. This contributes to almost 80% of the total amount spent on maintenance and operations in the US industry. In maintenance planning the main idea is to determine when to perform maintenance action on machines or parts of the machines used in the process. The decision on when to perform these actions may depend on different factors such as age of the machine, availability of resources, number of production cycles completed, number of failures.

There are different maintenance policies that are discussed in the literature and the most common ones include:

- Preventive Maintenance (PM) – **Carr and Christer (2003)** defined PM as the activities and actions that are carried out on a machine or a part on a planned or a periodic schedule to ensure that the machine is in a working condition. PM is ensured through a process of inspecting, checking and reconditioning.
- Corrective Maintenance (CM) – **Carr and Christer (2003)** defined CM as the activities and actions that are performed on a machine in an unscheduled interval. The trigger of CM is a failure, or a breakdown and the corrective actions are to put the machine back to a working state.
- Condition-Based Maintenance (CBM) – **Christer and Waller (1986)** defined CBM as the activities and actions performed on a machine based on a certain condition. In CBM usually the machine is monitored continuously using a device (a sensor for example) and whenever the state of the machine reaches a specific point maintenance action is performed.

1.2.1 Maintenance Terms

This section includes some of the terms in maintenance that will be used. The definitions of the terms are from the British Standard 1984 (BS3811:1984). The terms and their definitions are:

- Availability: The ability of equipment to successfully perform its required function at a stated instant of time or over a stated period of time.
- Breakdown: Failure resulting in the nonavailability of the equipment.
- Condition-based maintenance: The preventive maintenance initiated as a result of knowledge of the condition of equipment observed through routine or continuous monitoring.
- Corrective maintenance: The maintenance carried out after a failure has occurred and intended to restore equipment to a state in which it can perform its required function.
- Failure: The termination of the ability of equipment to perform its required function
- Inspection: The process of measuring, examining, testing, gauging, or otherwise detecting any deviation from specifications.
- Maintenance: The combination of all technical and associated actions by which equipment or a system is kept in, or restored to, a state in which it can perform its designated functions.
- Maintenance schedule: A comprehensive list of items (equipment) and the maintenance tasks required, including the interval at which maintenance should be performed.

- Planned maintenance: The maintenance organized and carried out with forethought, control, and the use of records to meet a predetermined plan.
- Preventive maintenance: The maintenance carried out at predetermined intervals or intended to minimize the probability of failure or the performance degradation of equipment.
- Repair: The restoration of equipment to an acceptable condition by the refurbishment, replacement, or overhaul of damaged or worn parts.
- Scheduled maintenance: The preventive maintenance carried out at a predetermined interval of time or number of operations, mileage, etc.

1.2.2 Cost Control and Reduction in Maintenance

There are many costs that are related to maintenance that need to be controlled and reduced. The costs can be directly or indirectly related to maintenance. Some of the costs that are associated with maintenance include:

- Labor costs
- Parts and equipment costs
- Downtime costs
- Maintenance costs
- Lost production costs

The direct maintenance costs are the costs that are related directly to the maintenance actions like spare parts, material, labor costs. The downtime and lost production costs are the costs raised from stopping the machine or equipment to perform the maintenance actions which may cause the production process to stop for a specific amount of time. A part of inventory's costs can be related to maintenance by keeping a number of parts and equipment that need to be replaced in case of a breakdown or a necessary maintenance action. An example of an indirect cost could be the quality cost, where the maintenance actions can affect the quality of the products. Over maintaining and under maintaining costs are usual and common when the ideology of cost control and reduction in maintenance is not considered in production systems and facilities.

In many maintenance problems in the maintenance the aim is to minimize the total maintenance cost over a period of time. The problem is to find the optimal time when the maintenance should be performed in order to minimize the maintenance cost with the given parameters of the problem.

Cost reduction in maintenance can be helpful in many aspects as reducing the product cost. There are different approaches and methodologies used to reduce the cost of maintenance where they usually study the system and design engineered approaches of tackling the maintenance actions in the system.

1.2.3 Preventive Maintenance and the Delay Time Model

Preventive maintenance (PM) is one of the most important policies where maintenance actions are executed at planned time intervals, with objective of preventing potential plant failures from occurring. For any PM, inspection is a necessary activity as it provides information on the status of the item checked to facilitate the determination and execution of repair and replacement decisions. Christer (1976) was the first to investigate the importance of inspection through the development of delay-time concept. This concept divides the failure process of an asset in to two stages. Stage 1 is the normal operating stage (from new to the point where a defect is identified by inspection). Stage 2 is the delay-time of the failure (from the point of defect identification to failure if the defect is unattended). If an inspection is performed during the delay-time of the failure, then identified defects could be removed or rectified before failure. Modeling the durations of these two stages allows us to find optimal inspection intervals that optimize a criterion function of interest. The delay time model is explained in detail in Chapter 3 along with supportive figures and illustrations.

1.3 Human Factors

Human Factors play a big role today in different systems. Humans are involved in almost all parts of production, maintenance, operations and inspections. The effect of humans in maintenance and operations is significant. A study was performed on 213 maintenance problems reports in **Robinson et al. (1970)** to understand the human effect on these

problems. The study concluded that almost 25% of the maintenance problems were due to human errors. Another study performed by the International Civil Aviation Organization that was performed in 1993 on 122 maintenance actions involving humans' states that the main human errors that are involved in the maintenance are categorized as follows: Omissions (56%), wrong installations (30%), wrong parts (8%), others (6%). Another study mentioned by **Marx (1998)** and **Dhillon (1990)** by Boeing states that almost 19% of inflight engine shutdowns are caused by improper maintenance actions and errors. **Christensen and Howard (1981)** showed a study in the airline industry in the DC-10 aircraft accident that happened in Chicago in 1979, the investigation showed that the 272 people that were onboard died and the main reason behind the accident was that workers followed wrong procedures in the maintenance actions performed prior to the plane take off. In the US the costs associated with maintenance errors contribute to over $1 billion annually. **Marx (1998)** also mentioned a study that shows the maintenance error contributes to almost 15% of accidents in the aviation industry in the US.

In the nuclear industry errors cause significant losses and tragedy. Between the years 1965 and 1995 a study was performed in Japan's nuclear power plants by **Hesegawa et al. (1998)**. The study included almost 200 human errors that occurred. The investigations concluded that around 50% of the errors where because of maintenance activities. Another study by **Reason (1997)** that was performed on 126 error related events in the nuclear industry showed that 42% of the errors were caused by maintenance activities.

In the fossil plants industry, a study by **Daniels (1985)** showed that around 20% of faults occur due to human and maintenance errors. These errors contribute to 60% loss of power annually. One more study that was performed by **Pyy (2001)** on a boiling water reactor in the nuclear industry concluded that almost 7.5% of errors and faults are due to human errors in the maintenance actions performed.

All these studies show the significant impact of maintenance actions and human error. The studies are divided into two groups, either the impact of maintenance actions and activities on the systems and industries or the impact of the human error in the maintenance actions performed on the systems in the industries. These incidents and accidents increased the interest in studying ways of reducing and getting rid of the maintenance errors and human errors. Especially that some of the industries are very sensitive and errors don't only mean extra cost but can be fatal.

The terms in human reliability, error, and human factors that are used are explained next:

- Human reliability: This is the probability of accomplishing a specific task successfully by humans at any required stage in system operation within a defined minimum time limit.
- Human factors: This is a body of scientific-related facts concerning the characteristics of humans. The term includes all psychosocial and biomedical considerations. It also includes, but is no way restricted to, personnel selection, training principles and applications in the area of human engineering, human performance evaluation, aids for task performance, and life support.

- Human error: This is the failure to perform a specified task (or the performance of a forbidden action) that could result in disruption of scheduled operations or damage to equipment and property.
- Safety: This is conservation of human life and its effectiveness, and the prevention of damage to items as per specified mission requirements.
- Human performance: This is a measure of actions and failures under given conditions.
- Human performance reliability: This is the probability that a human will satisfy all stated human functions subject to specified conditions.
- Reliability: This is the probability that an item will perform its specified function adequately for the desired period when used according to the stated conditions.

1.4 Thesis Objectives

The primary objective of this thesis is to develop two mathematical models that integrate human factors in to delay-time modeling. Both models extend previous work by **Carr and Christer (2003)** to more realist conditions. The secondary objective is the application of fuzzy logic in the delay-time modeling. These objectives can be achieved by the following steps:

- Review of past research conducted in the areas of delay time model and human factors (i.e., human errors).
- Identify the human factors that have great impact on worker performance in maintenance.

- Develop a mathematical model that incorporates human factors in the form of inspection time (that previously was assumed constant) using fuzzy logic.
- Develop a mathematical model that incorporates human factors in the form of delay time and inspection time (that previously was assumed constant) using fuzzy logic.
- Present examples from the literature to illustrate the utility of both models.
- Conduct sensitivity analysis to study the effect of human factors on delay time modeling and compare the results to findings from the literature.

1.5 Thesis Organization

The organization of the thesis after the introduction chapter is as follows: Chapter 2 reviews the literature of the related topics that include delay time model, fuzzy logic in maintenance, human factors in maintenance and the performance shaping factors. Chapter 3 includes a conceptual classification model of the performance shaping factors affecting the maintenance activities. Chapter 4 includes the development of a delay time model that incorporates human factors in the form of inspection time. Chapter 5 includes the development of a delay time model that incorporates human factors for

both delay time and inspection time. Chapter 6 summarizes the work done in the thesis and recommends research avenues related to the area.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to illustrate the detailed literature review on the delay time modeling, fuzzy logic uses in maintenance, human factors integration into maintenance activities, and the performance shaping factors related to human factors.

The main aim is to consider the human factor integration into the maintenance policies used in the literature. The focus on human factors has raised as they contribute significantly in the maintenance activities in the manufacturing, aviation, and nuclear power plant industries. The next figure summarizes the division on the literature review chapter.

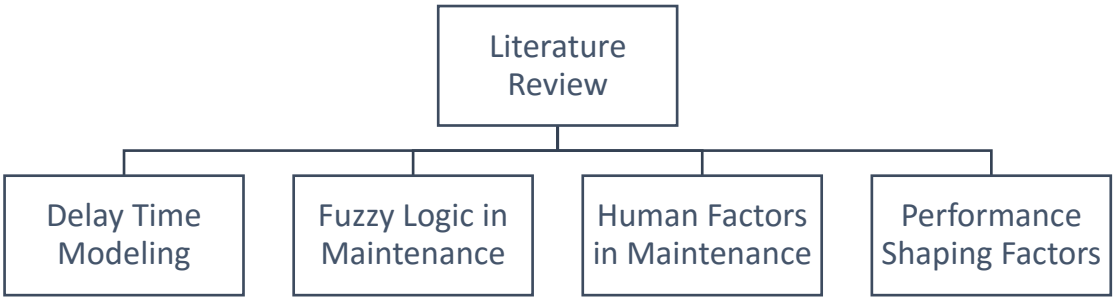

Figure 1: Literature Review Classifications

2.2 Delay Time Modeling

Baker and Wang (1992) considered the basic delay time model of Christer and Waller that used parameters that are estimated from subjective data. The contribution is that the used practical examples to provide an estimate of the parameters. In their model they used the method of maximum likelihood and the selected the best model using the Akaike Information Criterion (AIC). The data used are for an infusion pump and considered the history of breakdown times and inspection for the equipment. The results show that with a 95% confidence level the delay time model is a practical tool to optimize inspection policies based on the practical example.

Baker and Wang (1993) extended the work done earlier by relaxing the assumption that the age of the machine affects the period from replacement the equipment till the defect becomes detectible. Another extension provided is that the inspection is not always perfect and could have a negative effect on the lifetime of equipment.

Christer and Wang (1995) developed a model as an extension of the delay time model where the arrival of defects is a nonhomogeneous Poisson process. Another aspect considered in the model is that in a multi-component system, the inspection is not only performed on the planned interval but also whenever a component fails the inspection is performed

Wang and Christer (1997) proposed an extension to the previous work by considering a finite time horizon other than infinite. The proposed model considered a single failure mode and considered the consequences of the inspection in terms of safety. The consequences are proposed to be measured either by the probability of failure or as a cost incurred in the system.

Christer et al. (1998) suggested a model where the defects identified in the preventive maintenance action may not be eliminated completely. The parameters used in the delay time modeling are estimated using the maximum likelihood methodology from previous data of maintenance failures.

Pillay et al. (2001) studied the use of delay time modelling on maintenance activities of fishing vessels. The data used in the model are the operating and failure data which are collected from a real-life application. The outcome of the model is compared with the existing maintenance policy applied on the fishing vessel to show its effectiveness.

Wang and Christer (2003) presented different solution algorithms for a multi-component system using the delay time modelling. The first algorithm assumed that the fault arrivals are nonhomogeneous. The second algorithm extended the first one and assumed that the optimal inspection period is not constant. The third algorithm included a numerical algorithm for solving an integral equation to determine the inspection interval.

Carr and Christer (2003) formulated a model for taking human error into consideration when performing different maintenance policies using delay time modelling. The human error that was addressed in the model is in the form of fault injection during the inspection process of maintenance. The objective of the model is to determine the cost of human error on the maintenance process. The model is divided into three cases: One error may be injected, a number of faults maybe injected; the second case discuses complex maintenance systems where multiple human errors maybe applied in the inspection process, and fault injection is proportional to the duration of inspection; the third and last case discusses the relationship between the fault injection and the time spent in the inspection process of machine by the worker.

Lu and Wang (2006) proposed the use of delay time modelling on a production plant to determine the optimal inspection interval for preventive maintenance. The data used is collected from historical failure data at the plant to estimate the delay time distribution using the maximum likelihood.

Akbarov et al. (2008) proposed a process for decision making using delay time modelling. The process included different analytical tools including: regression analysis, snapshot modelling and delay time modelling.

Wang et al. (2010) built a model to determine the optimal maintenance policy using the delay time modelling. The contribution to the multi-component system is that each component and failure is modelled independently and then combined and pooled together to form a system. This is different to the regular multi-component systems where they assume a common delay time distribution for all the components.

Wang (2011) constructed a hybrid delay time model for spare parts and maintenance inspection. The models' aim is to optimize three decision variables; ordering quantity, ordering interval, and inspection interval. The ordering quantity and interval are related to the spare parts associated with the maintenance action to be performed.

Wang (2012) reviewed the literature related to the delay time modelling in the industrial plant maintenance activities. The review focused on the use of delay time modelling in

maintenance and included other modelling techniques and methodologies that are not related to maintenance

Oosterom et al. (2014) proposed a model for obtaining the optimal maintenance policy under the assumption of postponement of replacement when the defects are identified. This assumption shows the systems' utilization increases and there is a better window for preparation of maintenance resources (parts and technicians). Two models are built, a deterministic delay time and a more general delay time model.

Lopes et al. (2015) proposed policy for developing an inspection policy to be used in the equipment leasing industry. The developed policy helps in choosing the inspection program performing the inspection, and the maintenance response teams. The inspection policy is chosen using the delay time modelling concept.

Berrade et al. (2017) developed a model for a single component system using the delay time concept to optimize the system including postponed replacement. The postponement replacement conditions are explored to determine which conditions are cost effective. The postponement of replacement is under the assumption that inspection may interrupt the process and incur unnecessary costs.

Driessen et al. (2017) built a delay time model over an infinite horizon to minimize the average cost. The assumption of the model is that the inspections are imperfect and the probability of inspection errors alters over the systems operation time. The results show

that the model with constant probability of inspection error gives a higher cost than the developed model by almost 19%.

2.3 Fuzzy Logic and Systems in Maintenance Systems

Jeffries et al. (2001) developed a fuzzy method that substitutes the maximum selection technique for set truncation. The fuzzy method developed is referred to as min-max fuzzy inference method and its main objective is to reduce the wastage and maintenance overhead costs in the packaging industry. The main advantage of this method is that it is reliable and inexpensive to apply to the system.

Coudert et al. (2002) proposed an approach using fuzzy logic to cooperate in the performance of scheduling. Production and maintenance are used in the model they are usually conflicting when optimizing their integrated model. The approach gave a better satisfaction in the optimization of the two functions. Real data where used in a case study to show how the model behaves with the uncertainties.

Sergaki and Kalaitzakis (2002) built a fuzzy relationship database model that aims to rank thermal power systems inspection activities planning to take into consideration safety, reliability and variable operating conditions. The fuzzy logic is used to incorporate the linguistic terms along with the fuzzy inference to consider the experience of the workers in the system.

Sudiarso and Labib (2002) demonstrated an algorithm where fuzzy logic is used in a maintenance and a scheduling problem. The maintenance data to a shop floor problem are used in a fuzzy logic algorithm to get the optimal production system policy. The two input parameters in the fuzzy logic are: breakdown frequency and the average number of parts needed. The paper showed the algorithm with simulation to determine the optimal batch size.

Al-Najjar and Alsyouf (2003) studied the most common maintenance policies using a fuzzy multi-criteria decision-making method. The fuzzy logic input in the system helps in identifying the most efficient maintenance policy and approach. The results of the model are that the number of failures are reduced to zero, the planned replacements are reduced and the utilization of the component life cycle is increased.

El-Sharkh et al. (2003) formulated a mathematical model having a fuzzy model to incorporate the uncertainties in the system of power generation. The uncertainties involved are the load, fuel and maintenance costs. The paper proposed a fuzzy model with an evolutionary programming-based solution including a security constraint. Two models of the problem where the results of the technique: maintenance and security-constrained dispatch problems. The results gave a range of the optimal maintenance cost under the uncertainties.

Konstandinidou et al. (2006) presents the human reliability analysis using fuzzy classification to obtain the probability of error in maintenance actions and activities of a chemical plant. Cognitive reliability error analysis method (CREAM) is used for the human error reliability as it is precise, well-structured, and fits best when fuzzy logic is involved.

Yuniarto and Labib (2006) proposed a framework for integrating preventive maintenance and manufacturing control system. The fuzzy logic is used to help in the integration of the two systems. The contribution to this is the use of intelligent framework connecting the two systems together. The mean time between failures and the average time to failure are the two control agents used in the system.

Kuthamasu and Huang (2007) introduced a neuro-fuzzy model to solve condition based maintenance problem. It used Kullback-Leibler mean information to assess the problem and the effectiveness of the model developed is shown by applying it to real world cases.

Khanlari et al. (2008) used the fuzzy logic to prioritize the equipment used in the preventive maintenance actions. The prioritizing is not only for equipment, but all the resources needed in the activity. The fuzzy logic helped in interpreting the variables that cannot be quantified and statistically expressed in determining the priorities. The objective is to minimize the total cost for the preventive maintenance action and the associated costs including the inspection and the repair.

Ierace and Cavalieri (2008) applied and compared the fuzzy logic and analytical hierarch process on an Italian manufacturing entity. The main aim of the application is to help in the selection of the maintenance strategy to be used.

Derigent et al. (2009) presented a new fuzzy method to assess component proximity. This method is used in the design stage to impact the design out maintenance actions and activities. This methodology helps to study the non-planned maintenance actions and move it to before or after the planned maintenance by observing given components during their work.

Nodem et al. (2009) examined a production, repair and replacement problem for a manufacturing system. The machine in the system is subject to random breakdowns. A hierarchical decision-making approach is used in the system to find the optimal repair and replacement policy. The approach is based on a semi-Markov decision making model. The objective function of the model is to minimize the total cost incurred. Two approaches where used to demonstrate the benefits of the model: numerical examples and sensitivity analysis.

Lu and Sy (2009) proposed a fuzzy logic approach to be used in the decision making of maintenance system. The fuzzy logic used includes linguistic variables that include the experience of the workers working in the maintenance and manufacturing system. The model is injected into an internet-based system as a fuzzy agent.

Hennequin et al. (2009) addressed a problem of having a single stage and single product production system under imperfect maintenance. The maintenance policy used in the system is preventive maintenance and the imperfectness of the system depends on the worker performing the maintenance action. The factor that the system took into consideration is the experience of the worker and the time he takes to perform the maintenance action. The approach used was fuzzy logic which allows to take a range of experience in the model instead of is the worker experienced or not. The objective of the system is to minimize the cost per unit of time or increase the availability of the machine and the system as a whole.

Azadeh el al. (2010) studied a real case of pump failure and improved the maintenance process using fuzzy inference. The aim of the study is to provide a correct mechanism that could estimate the human reasoning. The fuzzy inference improves the maintenance process by improving the following elements: human error, repair time, expert knowledge used in training, unnecessary expenditures, and maintenance costs. The anticipated methodology is applied in a petrochemical industry.

Bashiri et al. (2011) modified the linear assignment method to accommodate the fuzzy logic in the system. The method developed is an interactive fuzzy linear assignment method to select the maintenance strategy. The data included are based on maintenance experts and helps the top management to select the suitable maintenance policy.

Duran (2011) extended the work in incorporating multiple criteria in the maintenance work by including the tangible and intangible factors into the decision-making process. The fuzzy analytical hierarchy process is used in a computerized maintenance management system to evaluate different options. After the model is developed a software prototype is developed to implement the method.

Verma et al. (2011) considered the fuzzy inference system in a multi-objective optimization framework using genetic algorithms. The system gives the decision maker many options where he can choose from in installing the corrective maintenance in the system. The options are based on the objectives set at the beginning of the plant and system.

Peng-Cheng et al. (2012) developed a fuzzy Bayesian network approach to enhance the quantification methodology of the organizational factors in the human reliability analysis. A framework is developed to link the organizational factors to human error. The developed framework is integrated with the Bayesian network to build the probability inference model of the human reliability analysis. The developed model helps in quantifying the relationships between the organizational factors and the human error and also in ranking and identifying the root causes of human error.

Baraldi et al. (2012) came up with a hybrid system of Monte Carlo method and fuzzy logic to assess the performance of a maintenance action. The fuzzy logic in the model

incorporates the input information of an expert of the effective age of the machinery. The hybrid system is applied on a case study of an electrical system.

Maatouk et al. (2016) combined fuzzy genetic algorithms and local search in a hybrid system to solve an optimization problem in preventive maintenance. The system optimized is a multi-state series and parallel system. The objective of the model is to optimize the maintenance policy for each component in the system by minimizing the cost function. The model took into consideration two main constraints, minimizing the cost function within a specific period of time and having an availability constraint for the machine.

Babashamsi et al. (2016) integrated fuzzy analytical hierarchy process and VIKOR method in a hybrid system for a pavement maintenance case in Tehran. The objective is to prioritize the maintenance activities for the process of a multi-criteria decision analysis. The fuzzy approach was used to determine the weights of the elements of the system including traffic, movement width, time needed, and maintenance cost. The results show that one of the streets that wasn't taken into consideration had the highest priority over the others examined together.

Hennequin and Restrepo (2016) considered a single stage single product failure in a manufacturing system. The objective of the paper is to minimize the maintenance cost and inventory along with the minimization of the environmental impacts. Fuzzy logic is

used to make sure the model is sustainable and be applied on the preventive maintenance policy.

Sarfraz (2017) describes the way to avoid breakdown in CNC's by using time based scheduled preventive maintenance for different parameters. The author reports that some of these parameters were determined from theoretical studies of material fatigue life and some from experimental data.

Ratnayake and Antosz (2017) developed a risk matrix to help in the classification of risk-based maintenance. The developed risk matrix helped in reducing the unexpected failures, the production lost, and the maintenance cost. Fuzzy logic is used to evaluate the consequences and prioritize the tasks based on the potential risk of failure for the maintenance tasks. the risk matrix is established in a way that it can be applied to already existing computer-aided maintenance management systems.

Kumar et al. (2017) applied the fuzzy logic on the human error assessment and reduction technique (HEART) on a refueling station maintenance actions. The fuzzy logic is used to define the expert's opinions into linguistic variables. The expert's input took place by putting weights to possible human error actions in the system. Results gathered from the study are compared across results obtained from CREAM. The approach is useful to incorporate the expert's input with uncertainties and vagueness.

2.4 Human Factors Integration in Maintenance

Su et al. (2000) developed a fault recovery management mechanism (FRMM) that integrates the reliability maintenance method with the expert system. The mechanism allowed the management and maintenance personal to detect fault cases accurately and faster. The data is collected through interviewing maintenance experts and analyzing tasks associated with maintenance activities. The FRMM model can be used as a guide to reduce human error in maintenance activities in logistic systems.

Kim et al. (2009) studied a case for a reactor in a nuclear power plant. The aim of the study was to determine the human errors during a test and maintenance actions. The study concluded that omission, wrong object, too little, and wrong action are the leading factors of human error in this case. Results of the study also showed that the human error is easily detected when in the execution phase but difficult to detect in advance. The detection of the human errors is based on human reliability methods.

Chang and Wang (2010) conducted a study to find out the important human factors that impact aircraft maintenance activities in the aviation industry. The study included a customized questionnaire that was filled by 107 professional maintenance workers. That study concluded that out of the 77 initial risk factors only nine of them are significant and impact the maintenance activities. The SHELL model that was initially developed by

Edwards in 1972 is modified to help in analyzing and ranking the important and significant human risk factors in the aviation industry.

Heo and Park (2010) estimated the qualitative and quantitative impacts in maintenance activities of human error in nuclear plants through a proposed framework. The framework helps the management in the decision-making process of the maintenance tasks and activities. The framework is divided into four parts: analyzing human error impact on the failure possibility, estimating the number of times the errors occur in the maintenance, fault tree analysis and simulation is used to estimate the risk of the errors, the abnormal power loss due to human error in the plant.

Khalaquzzaman et al. (2010) developed a model to estimate the unavailability of a component that is subject to failure due to human error in the maintenance activities. The model is to be used in a nuclear power plant and other industries as well. **Khalaquzzaman et al. (2010)** also developed a model that takes human error into consideration when working with maintenance and tests to evaluate the failure rates of components. The model is applied on a OPR-1000 reactor protection system and estimated the failure rate of the component during the maintenance action by considering the human error associated with the action.

Rashid et al. (2010) analyzed the human factors that affect helicopters maintenance activities. The sample size for the study is 58 helicopters. Root cause analysis is performed

to determine the human factors in the system. Classification system maintenance extension is obtained from the study with the root causes.

Liang et al. (2010) studied and developed an on-line maintenance assistance platform to increase the maintenance safety in the aviation industry. Human errors in each task are identified along with their risks and impacts. The results of the study showed that the workers job satisfaction, team risk understanding and awareness are increased using the developed platform of the on-line maintenance actions. The study was implemented and examined on an engine maintenance activity of a Boeing's 727 airplane.

Noroozi et al. (2012) determined and assessed the human error probabilities during a maintenance action on pumps. The human error assessment and reduction technique (HEART) is used to identify the human error probability during the maintenance action.

Kim and Park (2012) introduced a human error analysis procedure for humans when involved in maintenance actions. The analysis is based on the performance shaping factors the factors identified are evaluated for their possible impacts and the impact on the system that lead to failure during a maintenance action.

Noroozi et al. (2013) studied the significance of incorporating human error into pre- and post-maintenance activities of systems. The pre-maintenance is studied as the process of removing the parts and similarly the assembly and returning of parts and equipment is the post-maintenance action. Different scenarios have been considered in these two

processes and all the potential failures are identified. Success likelihood index method is used to quantify the human error and to find the human error probability along with the impact on the system.

Asadzadeh and Azadeh (2014) integrated a model of human error in a condition based maintenance. The objective of this model is to minimize the average unit cost of the system. the performance influencing factors in the system are identified and fed into the model as a failure probability.

Bao and Ding (2014) reviewed and investigated 3783 incident reports in the year of 2008 in the aviation industry with regards to maintenance. The incident reports include faults from maintenance workers and non-maintenance operators. Two methods are used in analyzing the data, maintenance error decision aid and correspondence analysis, to find the maintenance errors and the human factors contributing to these errors. Results of the investigation show that human error has significant impact for both maintenance and non-maintenance workers. Results also conclude that the factors are not only from the individual performing the maintenance but also from the decisions made at the top management and should be looked at more carefully.

Botelho et al. (2014) considered the intelligent maintenance systems (IMS) and injected the worker skills and environmental conditions as human factors that impact the maintenance activities. The model utilized the cyber physical systems approach to

capture the human factors. The approach is applied in two real life cases which are mobile robots for maintenance and mobile trucks in shipyards.

Pickthall (2014) examined the no fault found event during the maintenance actions. The maintenance human factors included in this study are based on data collected during an earlier study. The main objective of this study is to come up with a set of rules and standards for maintenance workers to follow when working with complex systems in the aviation industry.

Singh and Kumar (2015) investigated the human error during maintenance actions on a brake system on railways. The aim is to identify, asses, and minimize the human error probability on the system to improve the reliability and safety. The human error assessment and reduction technique (HEART) is used to identify the human error probability during the maintenance action. The main contributing factors to the human error in the system are found to be time pressure, ability to find fault, existence of over-riding information, differences between the designed model and the worker, and the need to make spontaneous decisions.

Abbassi et al. (2015) proposed a new way to determine the human error probability in maintenance operations. The methodology proposed integrates two well-known techniques which are success likelihood index method and the technique of human error

rate prediction. The methodology is applied on an offshore pump during its maintenance activities and the results show a 1.09% decrease in the human error probability.

Chiu and Hseih (2015) studied the human error that occur in maintenance activities of an aviation system. Human factors analysis and classification system and root cause analysis are the two techniques used to identify the main human errors in the system that could impact the maintenance process. results of the study show that coordination, communication, planning, physical limitations, mental limitations, and hostile physiological states are the most effecting factors in the maintenance action of an aviation system.

Shanmugam and Robert (2015) introduced a multi criteria decision making model and a scientific approach to evaluate maintenance actions in an aircraft. The model helps in applying the analytical hierarchy process to rank the important maintenance tasks and their potential human errors. The scientific approach is created based on data collected from a literature survey.

Abdul Hameed et al. (2016) extended their previous work and proposed a risk-based methodology to take into consideration the human error in approximating the maintenance interval and shutdown inspection. The methodology used to select the critical equipment in the system is a risk criticality matrix and the probability of human error is included using the success likelihood methodology. The developed methodology

is divided into three steps: selecting critical equipment, human error injection in the system failure model, and a risk-based shutdown inspection and maintenance interval estimation.

Emami-Mehrgani et al. (2016) extended the work of optimizing the preventive maintenance and corrective maintenance including the lockout and tagout. The effect of human error on the maintenance of the manufacturing system is studied where the system is exposed to random failure over infinite period. The objective for the model is to minimize the production cost subject to the maintenance actions and inventory levels.

Islam et al. (2017) modified and revised the human error assessment and reduction technique to incorporate the human errors in offshore operations. The approach included a new error production condition and error influencing factors that is based on surveys with experts from the marine industry. The developed approached is applied on a pump and an engine in an offshore oil and gas entity.

Sheikhalishahi et al. (2017) considered the case of maintenance planning with grouping strategy and human factors. Previously models have been formulated and applied without the consideration of humans. The results of the model show that fatigue and time pressure affect the performance of the ideal maintenance plan. The approach developed is also compared with genetic algorithm and simulated annealing.

Islam et al. (2018) formulated a model to incorporate human error in maintenance actions in marine systems. The effective human error probability model took into consideration internal and external factors that affect the performance of the workers performing a maintenance action on a ship. Some of the factors that were examined include: weather conditions, temperature, noise, vibration, and ship motion. The data collected for the model are based on experts' opinions who have been working for more than 5 years in marine systems. The model is used to come up with the human reliability with regards to the performance in the maintenance actions.

2.5 Performance Shaping Factors

Toriizuka (2001) examined maintenance activities in an industrial plant by considering a countermeasure to improve the work activities using performance shaping factors. The structural analysis of the performance shaping factors is not only used to determine the human reliability in the system but also to improve work efficiency and decrease workload on operators.

Hallbert et al. (2004) discusses how data related to performance shaping factors can be extracted from different sources. The sources include nuclear power plants licensee event reports, aviation safety reporting system, operator requalification data, improved

inspection team results, and results from psychological experiments from the literature. The discussion includes how to find the size of impact of the performance shaping factors, what are their relative impact on the system and how they interact.

Groth and Mosleh (2009) introduced a new hierarchical set of performance shaping factors in a nuclear power plant. The aim is to develop a model to quantify the impact of the performance shaping factors on the human errors. The data in the model are retrieved from the human events repository analysis database that is developed by the US nuclear regulatory commission. The model is a combination of the human reliability models, human performance theories, and data for human errors. The performance shaping factors in the model are independent meaning each can be measured alone and there is no overlap between them. The model resulted in six major categories containing 37 performance shaping factors.

Boring (2010) explored the importance of the performance shaping factors in the different phases of the human reliability analysis. These phases include the identification of possible errors caused by humans, developing a model for the errors using the probabilistic risk assessment, preventing potential errors, and turning the qualitative errors into quantitative ones.

Groth and Mosleh (2011) developed a methodology to ensure the dependency of the performance shaping factors in obtaining the human reliability analysis. The method

developed is a data informed Bayesian belief network that can be used to predict the human error probability while making sure the performance shaping factors are interdependent. The model developed replaces the linear calculations of human error probabilities and is customized in a way that whenever additional data is obtained it can be added easily. The Bayesian belief network is used as it supports the incorporation of professionals' judgement in the performance shaping factors.

Nascimento and Mesquita (2012) proposed a methodology to perform the human reliability analysis with shortages in data of human error. Performance shaping factors evaluation is performed along with the human reliability analysis based on the judgement of experts' in the same field. Experts' data is collected through questionnaires and interviews.

Kiyota and Okada (2015) studied the latent performance shaping factors and developed a method to assist in the characterization and analyzing potential human error and incidents. The study is performed in the following order: 1003 incident reports are analyzed from a petrochemical facility where human factors are involved in, based on the analysis 127 performance shaping factors are set, the factors set are classified into three groups related to how the operations are performed and nine groups related to the environment and the worker performing the operation, then keywords are set for each performance shaping factor, lastly a table containing all the performance shaping factors

is drawn where they are divided based on their categories and how each is analyzed for potential errors and incidents.

Liu et al. (2017) developed a risk-based approach to identify the performance shaping factors in a nuclear power plant. This approach focused on identifying the key performance shaping factors to be controlled by ranking the risk of each of the factors with regards to workers' performance. The application of the developed approach is used in a control room of a nuclear power plant to determine the frequency and impact of the performance shaping factors on the workers'. After the frequency and impact of each factor is determined, they are quantified by multiplying their perceived impact and frequency and ranked based on their risks according to the suggested performance shaping factors risk matrix. 33 workers are surveyed to take their input for the study. The performance shaping factors that received the highest scores are listed as high-risk level factors and are taken into consideration.

Kim et al. (2017) analyzed the human error and reliability in a low power and shutdown (LPSD) operation in a nuclear power plant. The objective of the analysis is to quantify the performance shaping factors when concerned with human reliability analysis in a LSPD task. The data is collected from a nuclear plant to determine the performance shaping factors that increase or decrease the human reliability and error. In the analysis a profile is given to each factor and root cause analysis methodology is used to describe each human error.

CHAPTER 3

INTEGRATED SYSTEM OF DELAY TIME MODEL WITH HUMAN FACTORS IN INSPECTION TIME

3.1 Introduction

Delay Time Modelling (DTM) was first introduced by Christer in 1976 as an idea. In 1984 the first application to the DTM in the industry was introduced and applied in a maintenance problem by Christer and Waller (1984). Following the application of the DTM in maintenance actions, extensions have been applied to the model to fit different real-life applications. Several models have been developed that include DTM for simple systems, complex systems, and systems with imperfections in inspection. Asset inspection modelling has been a hot topic for many years in the research. The very first model

developed was by Barlow and Proschan (1965) where they assumed an inspection model for a single unit. The inspection performed is perfect and at known intervals. If a defect or failure was found during the inspection, then action is taken to correct it and fix it. In this model the main problem is that if a failure occurred before the inspection time comes then it will stay down till the inspection period comes.

There are two main differences between the DTM and the classical Barlow and Proschan's model. The first difference is that if a defect or a failure occurs to the equipment it is identified and inspected as soon as it happens in the DTM but not in the classical model. The other difference is that after the defect is inspected the deterioration rate of the equipment changes and usually becomes faster and this is taken into consideration in DTM and not in the other model. Both models are applicable to different types of applications and they all have extensions that include Abdel-Hameed (1995), Kaio and Osaki (1989), McCall (1965).

The delay time modelling is defined as a two-stage model. The first stage starts when the defect becomes first detectible and the second stage is the period that the defect starts increasing till the failure occurs. The delay time is simply the period between the detection of the defect and the failure occurrence and is denoted by h. The next figure shows the two-stage model.

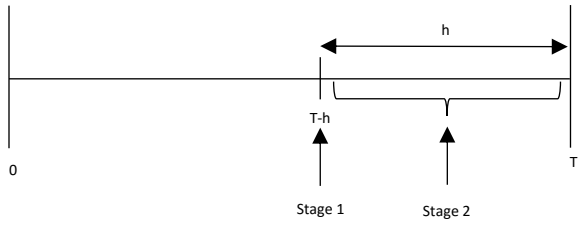

Figure 2: Delay Time Model

These identifications help in performing minimal repairs on these defects before the failure of the machine or equipment occurs. As soon as a defect happens it is inspected, and the needed changes are done so that the equipment continuous running till the preventive maintenance period comes and the repairing or replacement of parts is done. After the first defect occurs, the failure rate of the equipment starts increasing in an abnormal way as stated by Christer (1976). This abnormal increase in the failure rate, as explained before, is one of the main differences between the DTM and the basic asset inspection model by Barlow and Proschan.

3.2 Problem Statement

Consider a single machine manufacturing system that processes a set of jobs. The machine in the system is subject to failure due to different factors which include; deterioration, design of machine, external factors, and maintenance activities. In this problem, faults arise in the machine and they are repaired as failure repairs or inspection repairs. The failure of the machine results in lost production and therefore results in

production downtime D(T). Delay time analysis is used to model the effects of the inspection policies on time period T. The probability of faults becoming failures or machine breakdowns P(T) increases as the inspection period T increases.

The inspection activities are performed by maintenance operators, and inspection period varies depending on the operator performing the inspection task. The inspection performance in this problem is controlled by three factors; years of experience of operator, number of fatigue reports submitted by operator, and the seriousness level of the maintenance task. These three factors will contribute to the determination of the inspection period of the delay time model.

The problem that is being addressed here is to incorporate the human factors in modelling the inspection interval versus the production expected downtime. The main objective is to control the total machine expected downtime by including the effect of humans during the inspection period.

The approach in addressing the problem consists of building a fuzzy logic system that will allow us to determine the Human Factors, building the delay time model, integrating the output of the fuzzy system into the delay time model, applying a case study of the problem, and finally comparing results of the delay time model with the integrated model. This approach is included in the next sections.

3.3 Methodology

In this section the methodology of developing the integrated model is discussed. In order to develop the model, at first the performance shaping factors that affect the maintenance activities are identified and classified. After identifying the performance shaping factors, the model is explained and developed. The details of the methodology and the model development are explained next.

3.3.1 Performance Shaping Factors

The Performance Shaping Factors (PSFs) are all the elements that could affect the performance of a system. It is commonly used when humans are involved in the system. The PSFs helps in understanding all the elements and factors that affect the system as well as determine the human reliability and the chances of error occurring. In our system we will take into consideration the main performance shaping factors that influence the worker while performing the maintenance action on the equipment or machine.

Boring (2010) mentioned different categories in which the PSFs can be classified into. The first category is by splitting them into direct and indirect factors that affect the system. Direct PSFs are the factors of performance that can be measured directly when performing a task for example, time taken to complete a task. On the other hand, the indirect PSFs are the performance factors that can be measured through other measure for example, measuring fitness for a job or task through the fatigue level of the worker.

The second category that the PSFs can be classified by is internal and external factors that affect the system. This classification is the most commonly used, the next figure shows a representation of the internal and external factors with examples. The internal PSFs are those aspects that the person brings to the situation and include stress, mood, fitness, morale, etc. On the other hand, the external PSFs are the factors that influence the persons job or task from the surroundings. The maintenance environment is good example for the external factor and includes many aspects such as noise, temperature, illumination, etc.

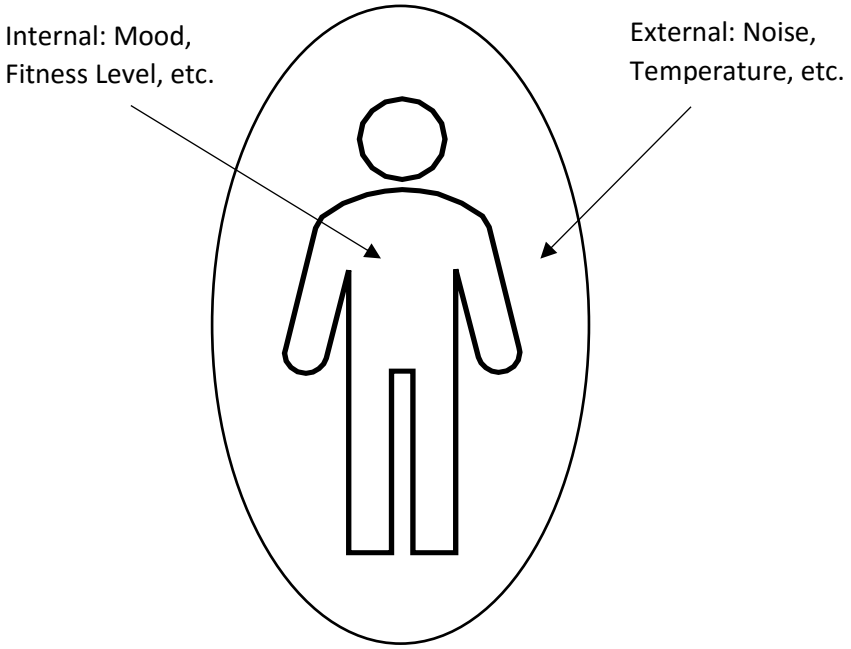

Figure 3: Internal and External Classification of PSFs

In order to understand the PSFs that can cause human error in maintenance actions, the next two tables include the common internal and external factors respectively with their explanations that are related to maintenance activities in the manufacturing industry.

#	PSF	Explanation
1	Experience	The number of years of experience or the experience level (low, medium, or high) of the worker performing the task
2	Stress	The physical, mental, or emotional factor that causes bodily or mental tension
3	Familiarity	The knowledge of the worker in the specific maintenance action
4	Fatigue	The condition resulting from insufficient rest
5	Training	The training level of the person performing the maintenance action
6	Morale	The amount of confidence felt by the operator while performing the maintenance action
7	Skills	The skill set needed to perform the maintenance action and his level of skills
8	Understanding of System	The overall understanding of the system with the parts, functions, and processes
9	Fear	The fear obtained from performing the job or from performing the job incorrectly
10	Complacency	The worker being over confident and working from memory rather than following procedure
11	Satisfaction	The personal satisfaction level of the job and performing the tasks
12	Distraction	The worker being distracted by personal issues
13	Assertiveness	The ability for the worker to express his feelings, opinions, and needs in a positive and productive manner
14	Time Spent	The time spent in the maintenance affects the performance, the more time spent the higher the chance of error

Table 1: Internal PSFs in Maintenance Actions

#	PSF	Explanation
1	Accessibility	The reach for the parts and equipment in the maintenance action
2	Noise	The maintenance action can be quite noisy and become uncomfortable while performing the task
3	Temperature	Maintenance actions could be performed in a not fully climate-controlled environment
4	Lighting	The illumination of the work place performing the maintenance action and the reach of light to the equipment
5	Peer Pressure	Pressure of performing the task correctly from co-workers and management
6	Team	The chemistry between the team members and the help of the team
7	Seriousness of Task	The hazard level while performing the maintenance action and the consequences resulting from a safety point of view
8	Complexity	The complication of the equipment that the maintenance action is performed on
9	Communication	The flow of communication and instructions between co-workers and from managers
10	Tools	The tools and equipment used in the maintenance action
11	Procedure	The written procedures for the maintenance action
12	Standards	The set rules and standards needed for performing the maintenance action
13	Motivation	The motivation, incentives, and appreciation received by superiors for performing tasks and jobs
14	Layout	The layout of the workplace and how easy is it to move around and reach equipment
15	Need for Special Tools	The need of special tools in specific maintenance actions
16	Design of Machine	The effect of the design of the machine and equipment on the maintenance action

Table 2: External PSFs in Maintenance Actions

The PSFs under the first hierarchy can be grouped further depending on the functionality or the attributes linking them. Internal PSFs are grouped into two groups; Person and Knowledge. On the other hand, external PSFs are grouped into two groups; Environment and System. The four PSF groups in shown in the next figure are the top level of the hierarchical PSF model. The second layer of the model is a set of 30 PSFs. The next table below the figure shows the grouping of the PSFs.

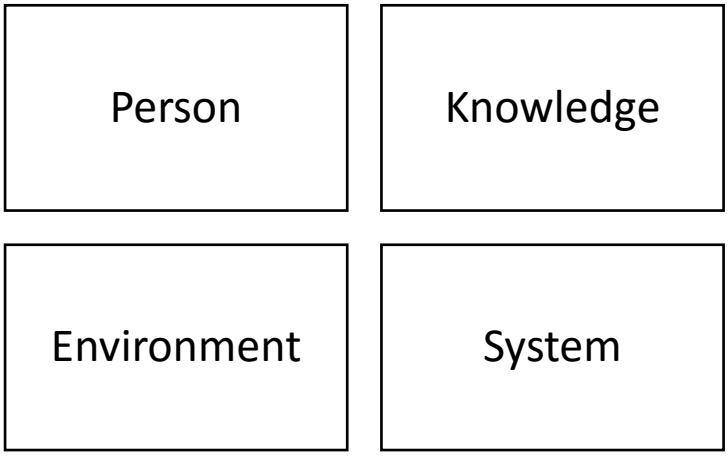

Figure 4: Top Level Hierarchy PSFs

Performance Shaping Factors					
Experience	Familiarity	Training	Skills	Time Spent	Understanding of System
Distraction	Fatigue	Morale	Fear	Satisfaction	Complacency
Assertiveness	Stress	Accessibility	Seriousness of Task	Complexity	Tools
Procedures	Standards	Layout	Need for Special Tools	Design of Machine	Noise
Temperature	Lighting	Peer Pressure	Team	Communication	Motivation

Table 3: Grouped Performance Shaping Factors

The top level and second hierarchy of the PSFs are summarized in the next figure. The top level PSFs are in the top and the second layer corresponding to each top level is under it.

Knowledge	Person	Environment	System
• Experience • Familiarity • Training • Skills • Time Spent • Understanding of System • Distraction	• Fatigue • Morale • Fear • Satisfaction • Complacency • Asseertivness • Stress	• Seriousness of Task • Accessibility • Complexity • Tools • Procedures • Standards • Layout • Need for Special Tools • Design of Machine	• Noise • Temperature • Lightning • Peer Pressure • Team • Communication • Motivation

Figure 5: Summary of Top Level and Second Level PSFs Hierarchy

The top level PSFs are explained as follows:

Person: Internal influencing factors that affect the person performing the maintenance action. These include characteristics of physical and mental state such as stress, fatigue, and morale. The Person PSFs are treated independently even though they can be linked to the Knowledge PSFs where they are the persons' readiness to apply the knowledge.

Knowledge: Internal influencing factors that affect the information needed to perform the maintenance action. The knowledge PSFs can be defined as the non-physical

resources of the personnel performing the maintenance actions. These include the level of experience, level of skills, and the training obtained.

System: External influencing factors that affect the performance and the comfortability of performing the maintenance action. These factors are usually a result of top management planning and execution where that standards, procedures, and layout design are set. The design of the machine itself and the easiness of accessibility of the parts and equipment affect the person performing the needed maintenance action

Environment: External influencing factors that affect the performance under certain conditions of maintenance actions. These include noise, temperature, and illumination when performing the maintenance actions. System PSFs are also a result of top management planning and execution. The effect of top management planning and execution is how the information is transferred, how are the personnel performing the maintenance motivated especially under extreme conditions, and how are the overall working conditions of maintenance actions.

3.3.2 Model Development

In this section, the delay time model is developed to incorporate the human factors using the fuzzy logic system in determining the inspection downtime. The main aim is to develop a model that predicts the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' downtime. This

section will include the development of the inspection downtime fuzzy logic system, expected downtime model, and the expected total cost model.

3.3.2.1 Inspection Downtime Fuzzy Logic System

In this section, a fuzzy logic model is designed and built to determine the factor for the Inspection downtime in the delay time model. The value for the inspection downtime is being assumed in the regular delay time model as a known and constant parameter. In real life this parameter depends on many factors, in this model we will use three of these factors experience, fatigue and seriousness as inputs to model the fuzzy logic system. The next three sub-sections explain the inputs' membership functions, outputs' membership functions, and the fuzzy rule base of the fuzzy logic system in details.

3.3.2.2 Establishing Membership Functions for the Inputs

The first step in building the fuzzy logic is determining the linguistic variables that will be used as inputs in the system. The definition of the linguistic variables and their groups differ for each PSF. The intended output is also defined as a linguistic term and its categories are defined later. Based on Ung et al. (2009), the membership function to be used in such problems is the triangular membership function. This type of membership results in a smooth transition from one state to another and makes the deffuzification easier of the linguistic terms used in the model.

The linguistic term that is used to describe the first PSF is the Experience of the worker performing the maintenance activity. The sets defining the experience of the worker are {Low, Medium, High}. This set represents the number of years of experience the worker has in the maintenance field. The interval of the experience of the worker is between 0 and 5 years of experience. The interval is set based on applications in the literature **Hennequin and Arango (2009),** experts that have worked in the maintenance in the manufacturing industry, and research done in different job hunting sites. The linguistic terms used for describing the experience of the worker (E) are as follows:

(a) E1 – Low
(b) E2 – Medium
(c) E3 – High

In order to model each of the experience levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next table. A graphical representation of the experience of workers membership function is illustrated in the Figure below the table.

Experience Level	Parameters		Function
E1 – Low	Minimum	0	Triangular {0, 0, 2.5}
	Mode	0	
	Maximum	2.5	
E2 – Medium	Minimum	0	Triangular {0, 2.5, 5}
	Mode	2.5	
	Maximum	5	
E3 – High	Minimum	2.5	Triangular {2.5, 5, 5}
	Mode	5	
	Maximum	5	

Table 4: Experience Level Parameters

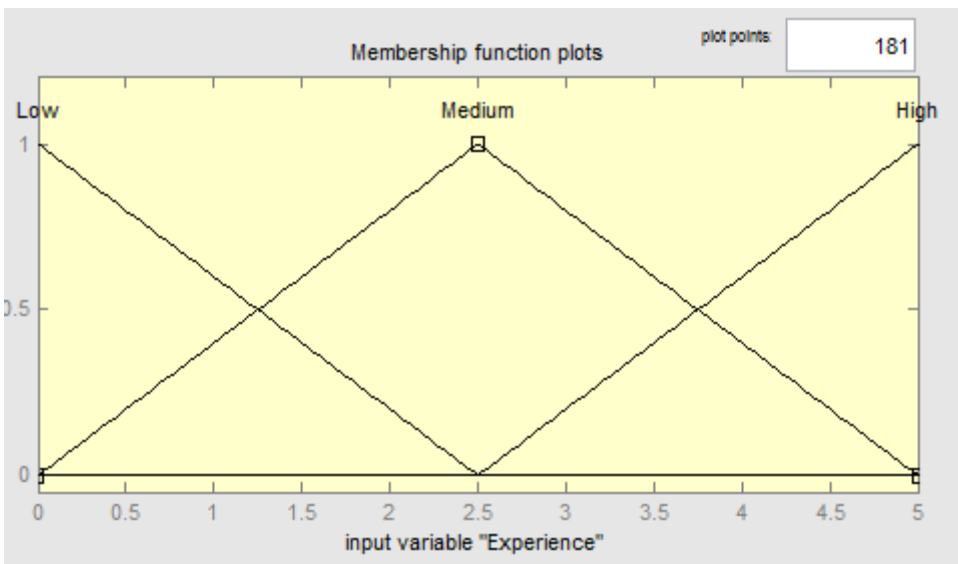

Figure 6: Experience Level Membership Function

The linguistic term that is used to describe the second PSF is the Fatigue of the worker performing the maintenance activity. The sets defining the fatigue of the worker are {Low, Medium, High}. This set represents the level of fatigue while performing the job. The interval of the fatigue of the worker is between 0 and 10 and is represented as the number

of fatigue incidents reported during the day. The interval is set based on applications in the literature as presented in **Peng-Chang et al. (2009).** The linguistic terms used for describing the fatigue of the worker (F) are as follows:

(a) F1 – Low
(b) F2 – Medium
(c) F3 – High

To model each of the fatigue levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next Table. These parameters are based on different applications from the literature and can be altered depending on the specific problem addressed. A graphical representation of the fatigue of workers membership function is illustrated in the Figure below the table.

Fatigue Level	Parameters		Function
F1 – Low	Minimum	0	Triangular {0, 0, 2.5}
	Mode	0	
	Maximum	5	
F2 – Medium	Minimum	0	Triangular {0, 2.5, 5}
	Mode	5	
	Maximum	10	
F3 – High	Minimum	5	Triangular {2.5, 5, 5}
	Mode	10	
	Maximum	10	

Table 5: Fatigue Level Parameters

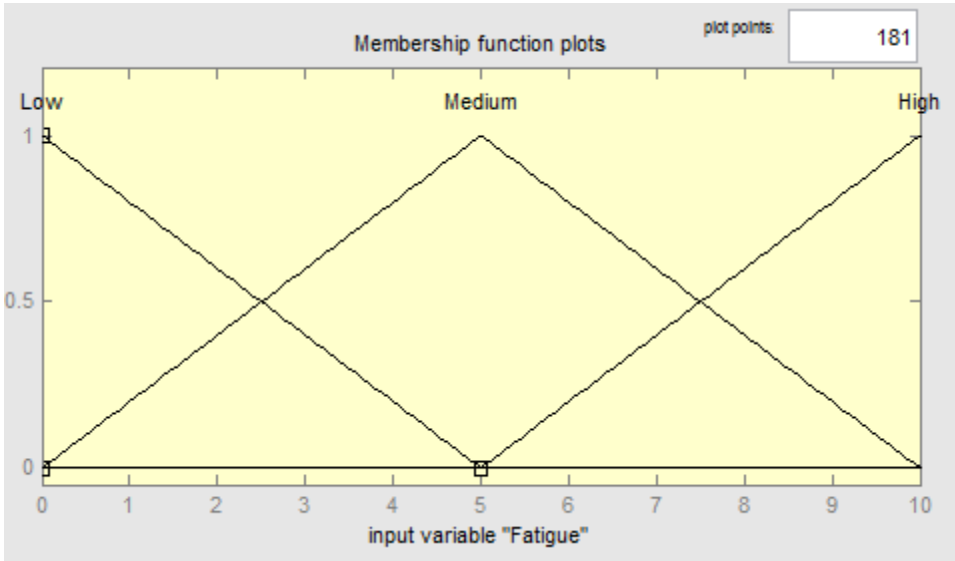

Figure 7: Fatigue Level Membership Function

The linguistic term that is used to describe the third and last PSF that will be used in this fuzzy system is the Seriousness of Task performed in terms of safety and injury that might result if an accident occurs. The sets defining the seriousness of task are {Class 1, Class 2, Class 3, Class 4}. This set represents the class the injury that might occur falls in. The linguistic terms used for describing the seriousness of the task (S) are as follows:

(a) C1 – Class 1
(b) C2 – Class 2
(c) C3 – Class 3
(d) C4 – Class 4

The definition of these classes are as follows:

- Class 1: Accidents that are treated locally using a first aid kit. These accidents usually result in less than 8 hours of work loss or less than a $100 of property damage.
- Class 2: Minor injuries that do not require the interference of a physician and usually result in more than $100 of property damage or 8 hours or more of work time.
- Class 3: Injuries that require the interference and treatment of a physician from outside the work place.
- Class 4: Accidents that include lost workdays, permanent partial disabilities and temporary total disabilities.

To model each of the seriousness of task level of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next Table. These parameters are based on different applications from the literature and can be altered depending on the specific problem addressed. The seriousness of the task is a subjective matter and it can be specified for each type of accident or injury independently. A graphical representation of the fatigue of workers membership function is illustrated in the Figure below the table.

Seriousness Level	Parameters		Function
C1 – Class 1	Minimum	1	Triangular {1, 1, 2}
	Mode	1	
	Maximum	2	
C2 – Class 2	Minimum	1	Triangular {1, 2, 3}
	Mode	2	
	Maximum	3	
C3 – Class 3	Minimum	2	Triangular {2, 3, 4}
	Mode	3	
	Maximum	4	
C4 – Class 4	Minimum	3	Triangular {3, 4, 4}
	Mode	4	
	Maximum	4	

Table 6: Seriousness of Task Levels Parameters

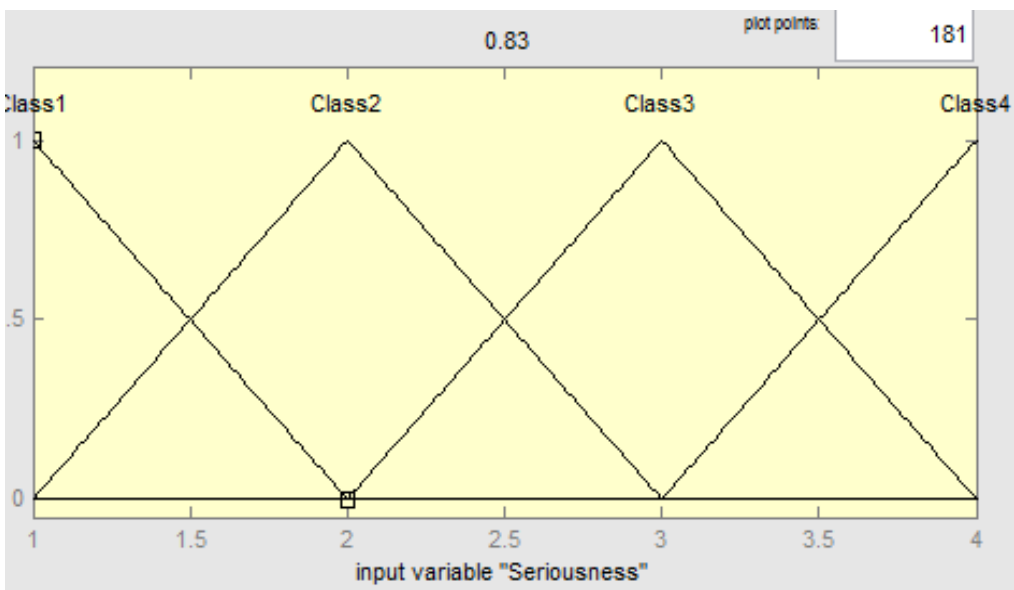

Figure 8: Seriousness Level Membership Function

Now that all the input linguistic terms have been defined along with their parameters, the output of the fuzzy model is to be defined in the next section.

3.3.2.3 Establishing Membership Functions for the Outputs

The output in our case is the consequence of all the inputs put together. In other words, how will the three-performance shaping factors affect the model. We will look at the output in terms of human factors on inspection time.

The output is defined as the effect of the human factors on the inspection downtime based on the experience of the worker, the fatigue level, and the seriousness of the maintenance task performed. The linguistic term that is used to describe the output of the fuzzy logic system is Human Factors. This factor has a range from 0 to 1 and will be used as an input in the delay time modelling presented in sections 4.2.2 and 4.2.3. The sets defining the human factor are {Very Low, Low, Medium, High, Very High}. These sets are used as follows to describe the human factor (HF):

(a) HF1 – Very Low
(b) HF2 – Low
(c) HF3 – Medium
(d) HF4 – High
(e) HF 5 – Very High

To model each of the human factor levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next Table. These parameters are subjective and based on different applications from the literature and can

be altered depending on the specific problem addressed. A graphical representation of the fatigue of workers membership function is illustrated in the Figure below the table.

Human Factors Level	Parameters		Function
HF1 – Very Low	Minimum	0	Triangular {0, 0, 0.25}
	Mode	0	
	Maximum	0.25	
HF2 – Low	Minimum	0	Triangular {0, 0.25, 0.5}
	Mode	0.25	
	Maximum	0.5	
HF3 – Medium	Minimum	0.25	Triangular {0.25, 0.5, 0.75}
	Mode	0.5	
	Maximum	0.75	
HF2 – High	Minimum	0.5	Triangular {0.5, 0.75, 1}
	Mode	0.75	
	Maximum	1	
HF3 – Very High	Minimum	0.75	Triangular {0.75, 1, 1}
	Mode	1	
	Maximum	1	

Table 7: Human Factors Levels Parameters

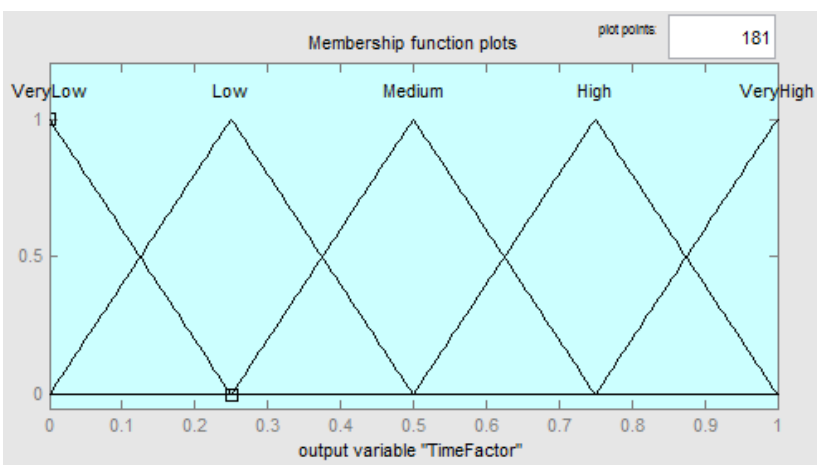

Figure 9: Human Factors Membership Function

The next figure summarizes all the inputs and output with their defined sets.

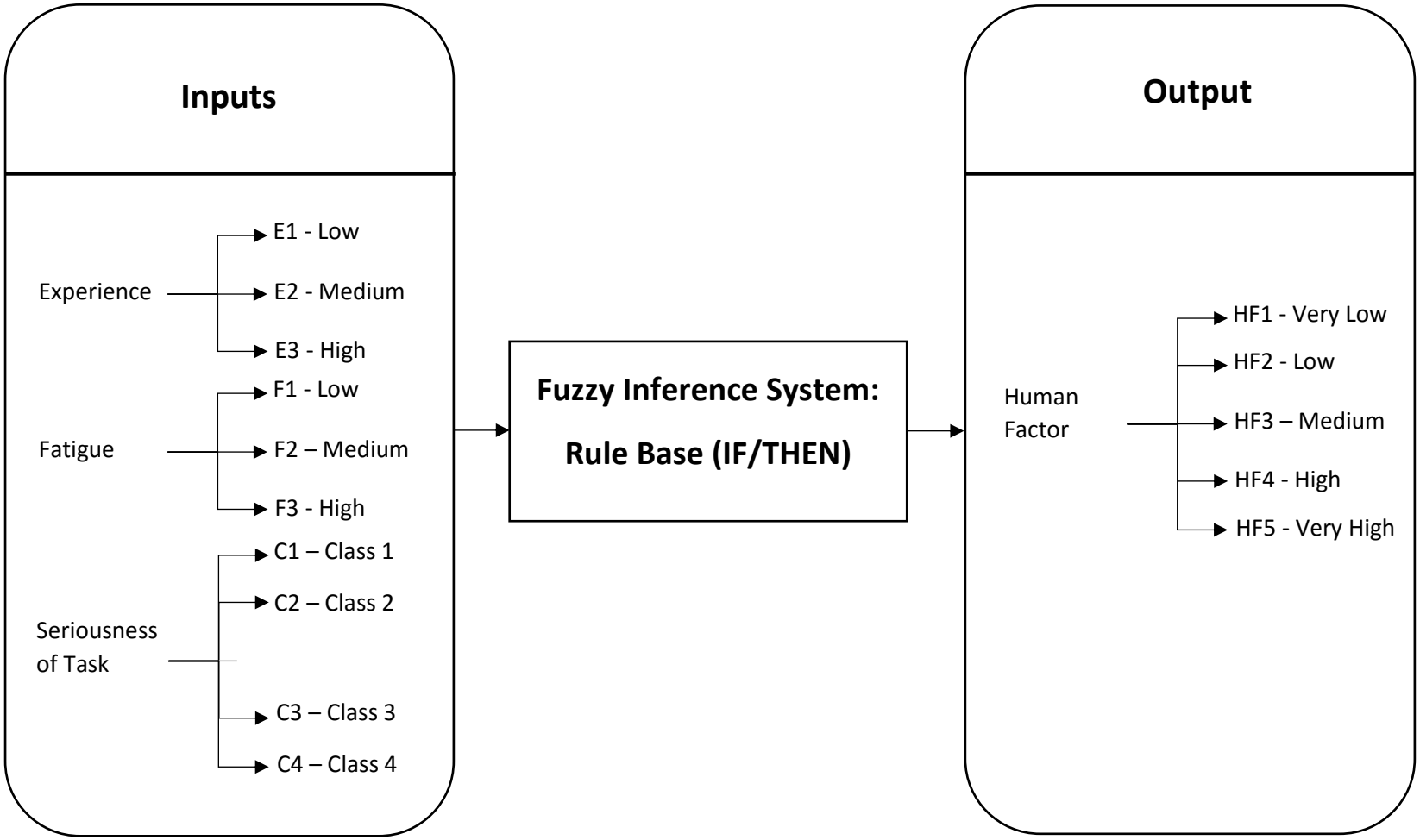

Figure 10: Human Factors Fuzzy System Summary

3.3.2.4 Developing a Fuzzy Rule Base

A fuzzy rule base is a system that is built in the form of IF/THEN rules. The IF part are the input variables that are defined in the previous section (Experience, Fatigue, and Seriousness of Task). The THEN part is the output variable that is defined earlier (Human Factor). The fuzzy rule base developed, given the number of years of experience, the fatigue level, and the seriousness of the task, assigns a human factor to the job (HF). An example of this is, IF Experience E2 is medium and Fatigue F1 is low and Seriousness C4 is Class 4 THEN Human Factor HF4 high is established given the results.

The number of rules that the system has is the product of all the possible combinations of sets of the linguistic variables. In this case the number of rules to be developed is determined as follows:

PSF	**No. of Classes**	**PSF**	**No. of Classes**	**PSF**	**No. of Classes**
Experience	{3}	Fatigue	{3}	Seriousness	{4}

Number of Rules = 3 x 3 x 4 =36 Rules

The evaluation and development of rules are purely subjective and depends on the logic. The method for setting the rules is divided into two steps as follows:

a) Set the first two inputs and evaluate the output;

At first the first two linguistic terms, Experience and Fatigue, are set and their logical corresponding output is chosen. This helps in more accurate results that will be fed to the next step to determine the final output and finalize the rule.

b) Add the third input and evaluate the final output;

After the preliminary output has been identified, it is used along with the third linguistic term, Seriousness of Task, to determine the output of the system. The following example shows how the rules are developed.

Example

a- Experience = E3 Fatigue = F1

Rule: IF experience E3 and fatigue F1 THEN human factor HF3

b- Seriousness of Task = C4

Rule: IF experience E3 and fatigue F1 and seriousness C4 THEN human factor HF3

All the rules are developed similar to the example and are illustrated in the next three Tables for E1, E2, and E3 respectively.

Rule #		Experience		Fatigue		Seriousness	THEN	Output
Rule 1	IF	E1	&	F1	&	C1	THEN	HF2
Rule 2	IF	E1	&	F1	&	C2	THEN	HF2
Rule 3	IF	E1	&	F1	&	C3	THEN	HF3
Rule 4	IF	E1	&	F1	&	C4	THEN	HF4
Rule 5	IF	E1	&	F2	&	C1	THEN	HF2
Rule 6	IF	E1	&	F2	&	C2	THEN	HF3
Rule 7	IF	E1	&	F2	&	C3	THEN	HF4
Rule 8	IF	E1	&	F2	&	C4	THEN	HF5
Rule 9	IF	E1	&	F3	&	C1	THEN	HF3
Rule 10	IF	E1	&	F3	&	C2	THEN	HF4
Rule 11	IF	E1	&	F3	&	C3	THEN	HF5
Rule 12	IF	E1	&	F3	&	C4	THEN	HF5

Table 8: Low Experience Rules

Rule #		Experience		Fatigue		Seriousness	THEN	Output
Rule 13	IF	E2	&	F1	&	C1	THEN	HF1
Rule 14	IF	E2	&	F1	&	C2	THEN	HF2
Rule 15	IF	E2	&	F1	&	C3	THEN	HF3
Rule 16	IF	E2	&	F1	&	C4	THEN	HF4
Rule 17	IF	E2	&	F2	&	C1	THEN	HF2
Rule 18	IF	E2	&	F2	&	C2	THEN	HF3
Rule 19	IF	E2	&	F2	&	C3	THEN	HF3
Rule 20	IF	E2	&	F2	&	C4	THEN	HF4
Rule 21	IF	E2	&	F3	&	C1	THEN	HF2
Rule 22	IF	E2	&	F3	&	C2	THEN	HF3
Rule 23	IF	E2	&	F3	&	C3	THEN	HF4
Rule 24	IF	E2	&	F3	&	C4	THEN	HF5

Table 9: Medium Experience Rules

Rule #		Experience		Fatigue		Seriousness	THEN	Output
Rule 25	IF	E3	&	F1	&	C1	THEN	HF1
Rule 26	IF	E3	&	F1	&	C2	THEN	HF1
Rule 27	IF	E3	&	F1	&	C3	THEN	HF2
Rule 28	IF	E3	&	F1	&	C4	THEN	HF3
Rule 29	IF	E3	&	F2	&	C1	THEN	HF1
Rule 30	IF	E3	&	F2	&	C2	THEN	HF2
Rule 31	IF	E3	&	F2	&	C3	THEN	HF3
Rule 32	IF	E3	&	F2	&	C4	THEN	HF3
Rule 33	IF	E3	&	F3	&	C1	THEN	HF3
Rule 34	IF	E3	&	F3	&	C2	THEN	HF4
Rule 35	IF	E3	&	F3	&	C3	THEN	HF5
Rule 36	IF	E3	&	F3	&	C4	THEN	HF5

Table 10: High Experience Rules

3.3.3 Expected Downtime Model Development

In this section, the delay time model is developed to incorporate the output of the fuzzy system presented in the previous section. The main aim is to develop a model that predicts the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' downtime. The objective for this model is to minimize the expected downtime. The inspection downtime is defined in regular delay time models as the time needed to perform the inspection. In this model the definition will be the minimum time needed to perform the inspection having perfect conditions (High Experience, Low Fatigue Level, Class 1 Seriousness). The notations that are used in this model are presented in the following table.

T	Inspection period
$P(T)$	Probability of defects detected rises to breakdown
$D(T)$	Expected downtime of system per unit time
k	Arrival rate of defects per unit time
d	Time needed to perform the inspection
H_f	Human factor associated with time of inspection
h	Delay time (time between fault arise and time of failure)
$f(h)$	Probability density function of delay time
d_b	Average downtime for breakdown repair

Table 11: Notations 1 Table

Now that the notations have been defined, the assumptions of the model are as follows:

a- Inspection action takes place every T time units and needs $(1+H_f)d$ time units. d is smaller than T $(d<<T)$.

b- Perfect inspection actions take place, meaning all defects and faults are recognized in the inspection action.

c- The delay time h is independent from the defect arrival time and its density function $f(h)$ is known.

d- Defect and failures arrivals follow a homogeneous Poisson distribution and they arise at a rate of k per unit time.

e- Defects identified are repaired in the inspection period, assuming maintenance operators are enough and available at all times.

f- H_f is the human factor from the operator performing the inspection task and depends on the experience, fatigue and seriousness of task.

The delay time process is shown in the next Figure. The defect arising is repaired as a breakdown repair if it occurs in the interval $(0, T-h)$, otherwise as an inspection repair if it occurs in the interval $(T-h, T)$. The inspection occurs every T time units and the faults arise in the interval $(0, T)$. The faults have a delay time in the interval $(h, h+dh)$. And the probability of this happening is given by $f(h)dh$

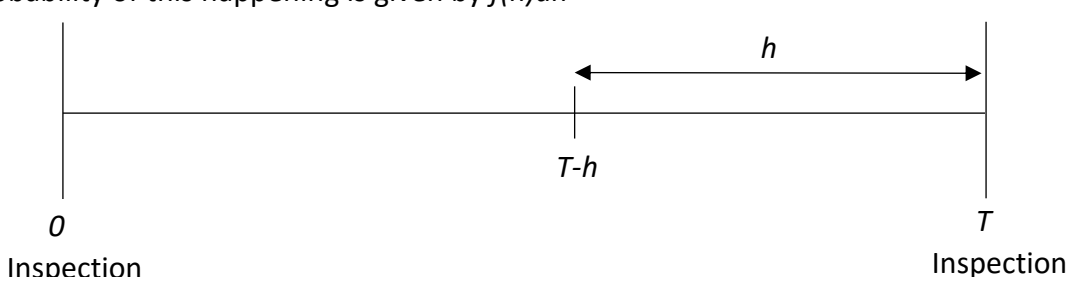

Figure 11: Delay Time Process

Assumption (e) states that all the repairs that are needed during the inspection are performed and finished within the given inspection period. Since the number of maintenance operators are enough, no matter how many repairs are to be performed it can be done if the operators work on the repairs simultaneously. The expected number of failures during the period *T* is given by:

$$Expected\ number\ of\ failures$$
$$= Arrival\ rate\ of\ defects\ per\ unit\ time * Time\ interval$$

$$Expected\ number\ of\ failures = kT$$

The expected number of failures is only when the machine is busy, therefore ignores the downtime due to breakdowns where there are no defects or faults occurring when the machine is idle.

The probability that a fault is repaired as a breakdown means that it occurs before *T-h* and this is described as:

$$probability\ of\ fault\ arising\ before\ T - h = \frac{T - h}{T}$$

This probability that the fault has a breakdown and has the delay time in (*h, h+dh)* is

$$\left(\frac{T - h}{T}\right) f(h)dh$$

Taking the probability over all values of h, it is given by

$$P(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f(h)dh$$

The expected downtime for breakdowns and inspection is given described as

$$Expected\ downtime = kTd_b P(T) + (1 + H_f)d$$

Then the expected downtime per unit time to be incurred in period *T* is *D(T)* where

$$D(T) = \frac{kTd_b P(T) + (1 + H_f)d}{T + (1 + H_f)d}$$

3.3.4 Expected Total Cost Model Development

In this section, the delay time model is developed to incorporate the output of the fuzzy system presented in the previous chapter. The main aim is to develop a model that predicts the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' cost. The objective for this model is to minimize the total expected cost.

The inspection cost is defined in regular delay time models as the cost needed to perform the inspection. In this model the definition will be the maximum cost that is needed to perform the inspection having the extreme conditions (High Experience, Low Fatigue Level, Class 1 Seriousness). The notations that are used in this model are presented in the following table.

T	Inspection period
$P(T)$	Probability of defects detected rises to breakdown
k	Arrival rate of defects per unit time
d	Minimum time needed to perform the inspection
H_f	Human factor associated with time of inspection
h	Delay time (time between fault arise and time of failure)
$f(h)$	Probability density function of delay time
C_b	Cost of breakdown repair
$C_b(T)$	Expected cost of breakdown repair
C_{pm}	Preventive maintenance action cost
$C_{pm}(T)$	Expected preventive maintenance cost
C_i	Maximum cost that is needed to perform the inspection
$C(T)$	Expected total cost per unit time

Table 12: Notations 2 Table

Now that the notations have been defined, the assumptions of the model are similar to the assumptions presented in the previous section as both models are the same and only the objective function differs. One assumption to emphasize on is that the cost of breakdown is higher than cost of preventive maintenance. The development of the model is as follows.

The expected number of failures during the period *T* is given by:

$$Expected\ number\ of\ failures$$
$$= Arrival\ rate\ of\ defects\ per\ unit\ time * Time\ interval$$

$$Expected\ number\ of\ failures = kT$$

The expected number of failures is only when the machine is busy, therefore ignores the downtime due to breakdowns where there are no defects or faults occurring when the machine is idle.

The probability that a fault is repaired as a breakdown means that it occurs before *T-h* and this is described as:

$$probability\ of\ fault\ arising\ before\ T - h = \frac{T - h}{T}$$

This probability that the fault has a breakdown and has the delay time in (*h, h+dh)* is

$$\left(\frac{T - h}{T}\right) f(h)dh$$

Taking the probability over all values of h, it is given by

$$P(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f(h)dh$$

In order to obtain the expected total cost, three costs are incurred in the model and they are:

$$\begin{aligned} &Expected\ total\ cost \\ &\qquad = Expected\ breakdown\ repair\ cost \\ &\qquad + Expected\ preventive\ maintenance\ cost \\ &\qquad + Inspection\ cost \end{aligned}$$

Where the expected breakdown repair cost denoted by $C_b(T)$ is given by

$$\begin{aligned} &E\text{xpected breakdown repair cost} \\ &\qquad = Breakdown\ repair\ cost * Expected\ number\ of\ breakdowns \end{aligned}$$

$$C_b(T) = C_b kTP(T)$$

Similarly, the expected cost of preventive maintenance denoted by $C_{pm}(T)$ is given by

$$C_{pm}(\mathrm{T}) = C_{pm} kT(1 - P(T))$$

The last element of the total cost is the inspection cost. The inspection cost C_i is assumed to be the ideal cost where an expert with no fatigue and the seriousness of the task is low

and this would result in the highest cost of all combinations. Adding the human factor into the inspection cost will result in the following expected total cost *C(T):*

$$C(T) = \frac{C_b kTP(T) + C_{pm} kT\big(1 - P(T)\big) + (1 - H_f)C_i}{T + (1 + H_f)d}$$

3.4 Numerical Example and Results

In this section, a descriptive illustration for the model developed earlier is shown using the data from the literature (**Carr and Christer**, **2003**). For the human factor (H_f), it is obtained using the fuzzy inference system described earlier. The fuzzy inference system was solved using MATLAB program.

Consider a manufacturing system with one machine that is subject to breakdowns. The machine has the following breakdown and failure parameters: the probability density function of the delay time follows a negative exponential distribution with the rate parameter (λ)= 0.05, the probability density function of the delay time is given as:

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

The breakdown downtime $d_b = 0.5$ hours, the inspection downtime $d = 0.35$ hours, and the average delay time $h = 20$ hours. The arrival rate of defects $k = 0.1$ defects per hour. Assume that the maintenance operator performing the inspection and maintenance has *3 years* of experience, he reported *2 fatigue reports* during the day, and the top management classify the machine's seriousness as *Class 3*. These parameters are used to determine the *T* that minimizes the expected total downtime *D(T).*

The first step in determining the expected total downtime, the human factor H_f is to be determined using the information given.

- Experience = 3 years
- Fatigue = 6 reports
- Seriousness = Class 3

These three parameters are used as inputs in the fuzzy inference system. The next figure shows the parameters set in the model.

Figure 12: Fuzzy Logic System Inputs

Running the fuzzy logic system with the specified inputs result in a human factor H_f value of 0.569 and this output from the system is shown in the figure below.

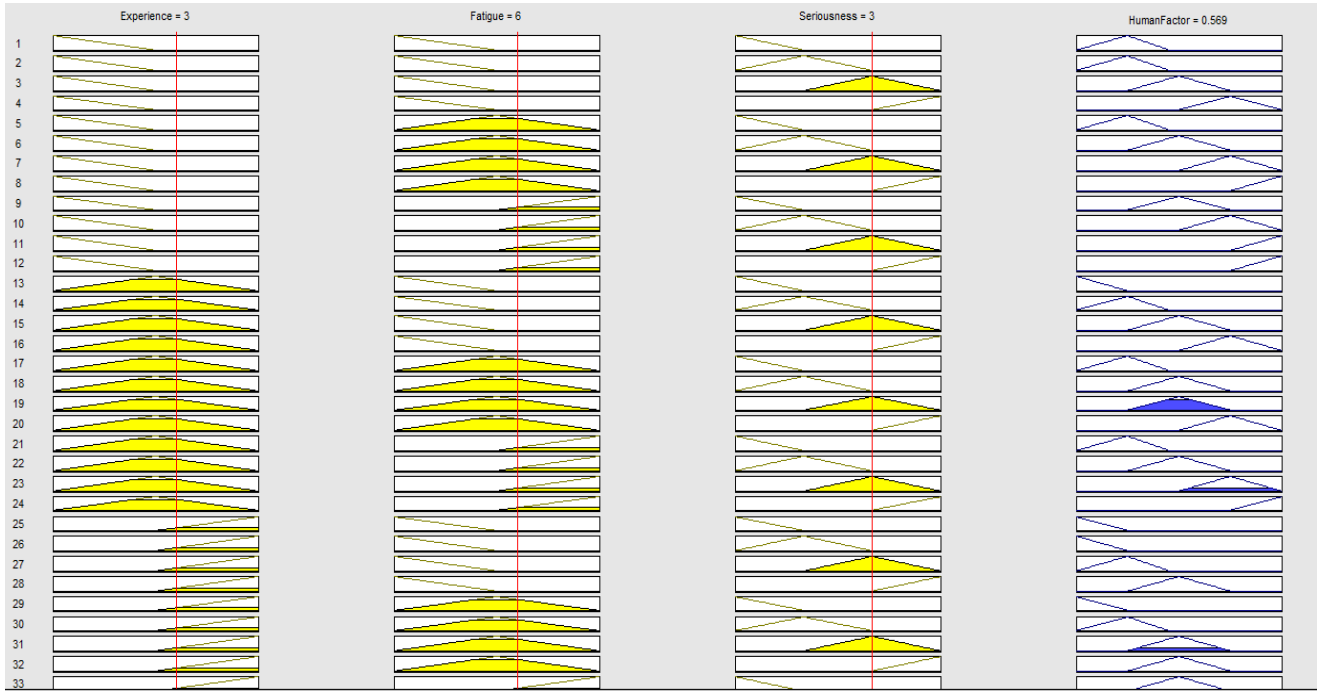

Figure 13: Fuzzy Logic I Output Results

Next step, is to implement the results of the fuzzy logic system into the delay time model along with the other parameters. These results will form the expected breakdown downtime per unit time of:

$$D(T) = \frac{kTd_bP(T) + (1 + T_f)d}{T + (1 + H_f)d}$$

$$D(T) = \frac{0.1 * T * 0.5 * P(T) + (1 + 0.569) * 0.35}{T + (1 + 0.569) * 0.35} = \frac{0.05 * TP(T) + 0.5492}{T + 0.5492}$$

The probability that a fault has a breakdown *P(T)* is obtained using:

$$P(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f(h)dh$$

Where *f(h)* is

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

Resulting in *P(T):*

$$P(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) \lambda e^{-\lambda h} dh$$

$$= \int_{h=0}^{T} \left(\frac{T-h}{T}\right) 0.05 e^{-0.05h} dh$$

The next table shows the values of *P(T)* with their corresponding *T* values:

T	P(T)	T	P(T)	T	P(T)
1	0.024588	34	0.519226	67	0.711965
2	0.048374	35	0.527871	68	0.715698
3	0.071387	36	0.536277	69	0.719347
4	0.093654	37	0.544453	70	0.722914
5	0.115203	38	0.552405	71	0.726401
6	0.136061	39	0.560141	72	0.729812
7	0.156252	40	0.567668	73	0.733148
8	0.1758	41	0.574993	74	0.736412
9	0.194729	42	0.582122	75	0.739605
10	0.213061	43	0.589062	76	0.742729
11	0.230818	44	0.59582	77	0.745787
12	0.248019	45	0.6024	78	0.74878
13	0.264686	46	0.608808	79	0.75171
14	0.280836	47	0.615051	80	0.754579
15	0.296489	48	0.621132	81	0.757388
16	0.311661	49	0.627059	82	0.76014
17	0.326371	50	0.632834	83	0.762835
18	0.340633	51	0.638463	84	0.765475
19	0.354464	52	0.643951	85	0.768062
20	0.367879	53	0.649302	86	0.770597
21	0.380893	54	0.654521	87	0.773082
22	0.393519	55	0.65961	88	0.775518
23	0.405771	56	0.664575	89	0.777905
24	0.417662	57	0.669419	90	0.780246
25	0.429204	58	0.674146	91	0.782542
26	0.440409	59	0.678759	92	0.784794
27	0.451289	60	0.683262	93	0.787002
28	0.461855	61	0.687659	94	0.789169
29	0.472117	62	0.691951	95	0.791295
30	0.482087	63	0.696144	96	0.793381
31	0.491773	64	0.700238	97	0.795429
32	0.501185	65	0.704238	98	0.797438
33	0.510333	66	0.708146	99	0.799411

Table 13: Probability values with respect to time T

The table below shows the values of *T* and their corresponding *D(T)* using the P(T) from the previous table.

T	D(T)	T	D(T)	T	D(T)
1	0.355278	34	0.041443379	67	0.043439
2	0.217322	35	0.04143345	68	0.043509
3	0.157744	36	0.041435954	69	0.043579
4	0.124832	37	0.041449332	70	0.043648
5	0.104151	38	0.041472215	71	0.043716
6	0.090083	39	0.041503397	72	0.043784
7	0.079988	40	0.041541815	73	0.04385
8	0.07246	41	0.041586528	74	0.043916
9	0.066684	42	0.041636706	75	0.04398
10	0.062155	43	0.04169161	76	0.044044
11	0.058541	44	0.041750587	77	0.044107
12	0.055618	45	0.041813057	78	0.044168
13	0.053228	46	0.041878506	79	0.044229
14	0.051256	47	0.041946474	80	0.044289
15	0.049618	48	0.042016553	81	0.044348
16	0.048249	49	0.042088383	82	0.044407
17	0.0471	50	0.042161639	83	0.044464
18	0.046133	51	0.042236034	84	0.04452
19	0.045316	52	0.042311314	85	0.044576
20	0.044626	53	0.04238725	86	0.04463
21	0.044043	54	0.042463641	87	0.044684
22	0.04355	55	0.042540306	88	0.044737
23	0.043135	56	0.042617087	89	0.044789
24	0.042785	57	0.042693842	90	0.04484
25	0.042493	58	0.042770445	91	0.044891
26	0.042249	59	0.042846786	92	0.04494
27	0.042048	60	0.042922767	93	0.044989
28	0.041884	61	0.042998302	94	0.045037
29	0.041751	62	0.043073314	95	0.045085
30	0.041647	63	0.043147739	96	0.045131
31	0.041567	64	0.043221517	97	0.045177
32	0.041508	65	0.0432946	98	0.045222
33	0.041468	66	0.043366943	99	0.045266

Table 14: Expected Downtime with respect to time T

After obtaining the expected downtime for each inspection period, the inspection period is plotted against the expected downtime. The next figure illustrates the results.

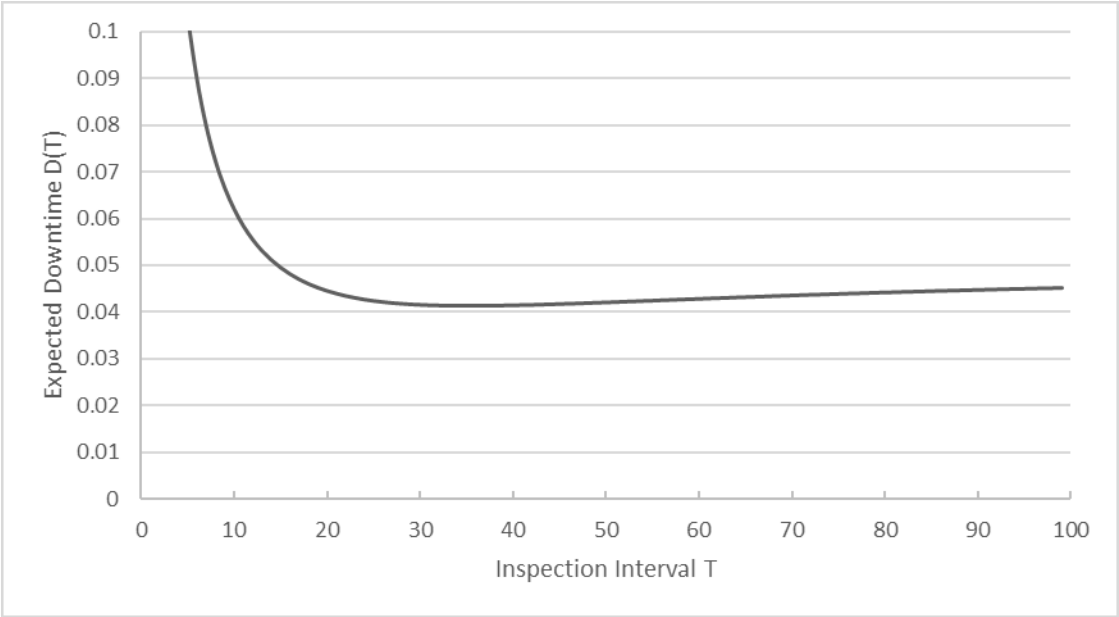

Figure 14: Expected Downtime Vs. Inspection Interval T

The results show that the inspection interval that gives the minimum expected downtime for this problem is T= 35 hours. This means that inspection will take place every 35 hours and will have an expected downtime because of failure D(T)= 0.04143.

Using the same parameters stated at the problem definition we determine the expected total cost per unit *C(T).* Assume that the Cost of breakdown repair C_b = 5000, Cost of preventive maintenance C_{pm} = 2000, and the Inspection cost C_i =2500. The expected total cost per unit is obtained using the expected total cost equation obtained in the previous section. Applying the parameters into the equation:

$$C(T) = \frac{C_b kTP(T) + C_{pm} kT\big(1 - P(T)\big) + (1 - H_f)C_i}{T + (1 + H_f)d}$$

$$= \frac{5000 * 0.1 * TP(T) + 2000 * 0.1 * T\big(1 - P(T)\big) + (1 - 0.569)2500}{T + (1 + 0.569)0.35}$$

$$= \frac{500TP(T) + 200T\big(1 - P(T)\big) + 1077.5}{T + 0.5492}$$

The method of obtaining the time interval *T* that minimizes the expected total cost per unit time is through numerical analysis. The values of P(T) are used from previous table and the table below shows the values of *T* and their corresponding *C(T).*

T	C(T)	T	C(T)	T	C(T)
1	861.4411	34	382.7366562	67	426.9133
2	610.4582	35	384.5315193	68	427.8297
3	504.7329	36	386.2994989	69	428.727
4	448.3276	37	388.0393564	70	429.6056
5	414.4652	38	389.7501427	71	430.466
6	392.728	39	391.4311541	72	431.3085
7	378.2219	40	393.0818944	73	432.1338
8	368.346	41	394.7020438	74	432.9421
9	361.5918	42	396.2914317	75	433.734
10	357.0249	43	397.8500142	76	434.5097
11	354.0368	44	399.3778546	77	435.2698
12	352.2147	45	400.8751063	78	436.0146
13	351.2692	46	402.341999	79	436.7445
14	350.9921	47	403.7788262	80	437.4598
15	351.2298	48	405.1859347	81	438.161
16	351.8669	49	406.5637154	82	438.8484
17	352.8156	50	407.9125958	83	439.5223
18	354.0078	51	409.2330329	84	440.183
19	355.3899	52	410.5255074	85	440.8309
20	356.92	53	411.7905191	86	441.4663
21	358.5641	54	413.028582	87	442.0896
22	360.2952	55	414.2402209	88	442.7009
23	362.0914	56	415.425968	89	443.3006
24	363.9348	57	416.5863601	90	443.8891
25	365.8108	58	417.7219365	91	444.4665
26	367.7073	59	418.8332367	92	445.0331
27	369.6145	60	419.9207984	93	445.5892
28	371.5244	61	420.9851565	94	446.1351
29	373.4303	62	422.0268415	95	446.671
30	375.3265	63	423.0463785	96	447.1971
31	377.2087	64	424.044286	97	447.7137
32	379.073	65	425.0210757	98	448.2211
33	380.9165	66	425.9772515	99	448.7193

Table 15: Expected Total Cost with respect to Time T

After obtaining the expected downtime for each inspection period, the inspection period is plotted against the expected downtime. The next figure illustrates the results.

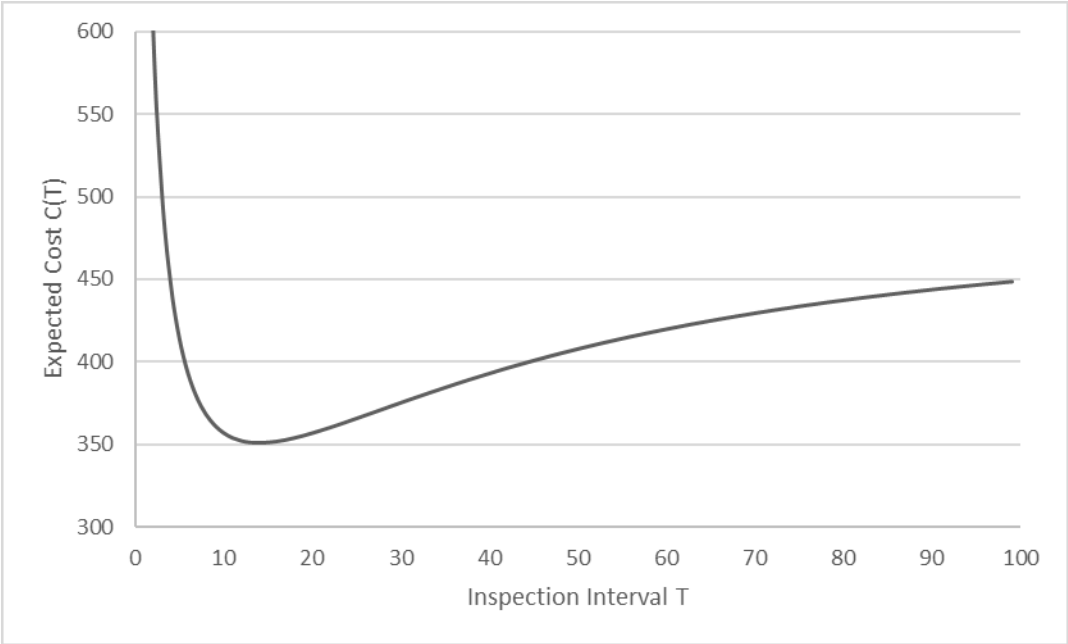

Figure 15: Expected Total Cost Vs. Inspection Time T

The results show that the inspection interval that gives the minimum expected cost with the assumed costs for this problem is T= 14 hours. This means that inspection will take place every 14 hours and will have an expected cost C(T) = 350.992.

3.5 Validation and Analysis

After developing the model and obtaining the results of the model, the next part is to perform a validation and analysis. The analysis is performed to compare the results to the base model. The details of the validation and analysis are discussed next.

3.5.1 Comparing Results

This section will illustrate the results of the developed model compared to base original model developed by (**Carr and Christer**, **2003**). The original and modified models were solved to determine the optimal inspection interval T to obtain the minimum expected downtime D(T). The next figure shows the results of the two models.

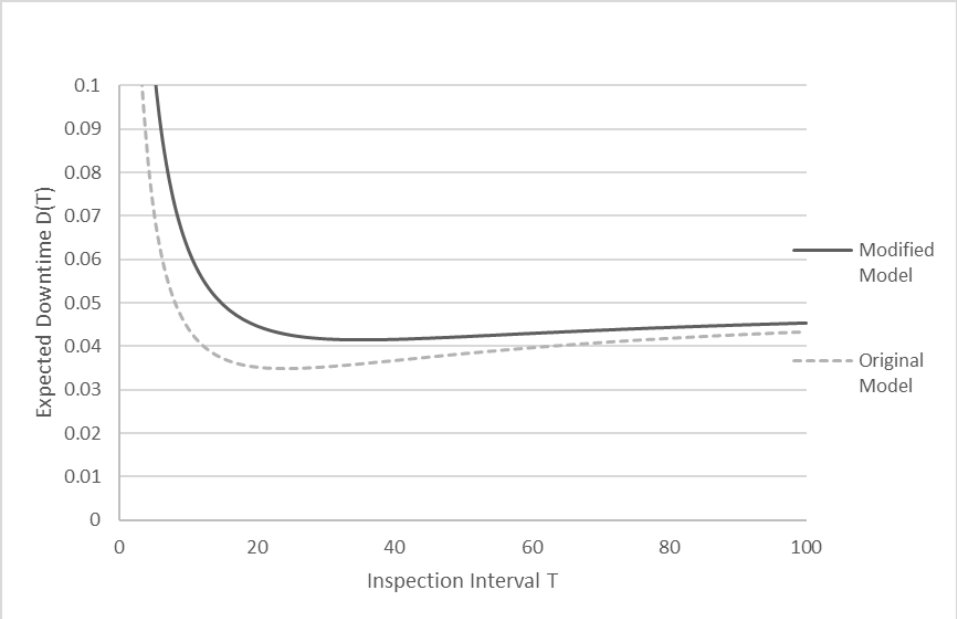

Figure 16: Comparison between original and modified expected downtime

The optimal T that minimizes the downtime for the original model is to perform inspection every 24 hours. On the other hand, the developed modified model proposes to perform inspection every 35 hours. These results show how often will the manufacturing process be interrupted. If we take a period of one month (30 days) then the original model suggests interrupting the manufacturing process for inspection 30 times. On the other hand, the modified model suggests interrupting it almost 21 times. If a cost is set to each time the process is interrupted, say calibration and set up of machine cost of 1000 then:

Model	Cost per interruption	No. of interruptions	Total Cost
Original Model	1,000	30	30,000
Modified Model	1,000	21	21,000

Table 16: Total cost of original and modified models

The table above shows the cost saved when set up cost is set for every time an inspection takes place. The modified model shows that the manufacturing process will be interrupted 9 times less than the original model with a saving of 30% cost associated with the interruptions.

The expected downtime for the original model when having inspection every 24 hours is 0.035 and 0.0414 for the modified model having inspection every 35 hours. The increase between the original model and the modified model is 0.0064 which accounts for 18.5%. It is true that there is an increase of almost 18.5% but the expected downtime value is relatively small.

Looking at the cost function and its results, the next figure shows the results of both models' original base and the modified one. The figure clearly shows that the modified model has a lower cost function. What we are interested in is the total cost incurred by the original model by performing inspection every 24 hours and the total cost incurred by the modified model by performing inspection every 35 hours.

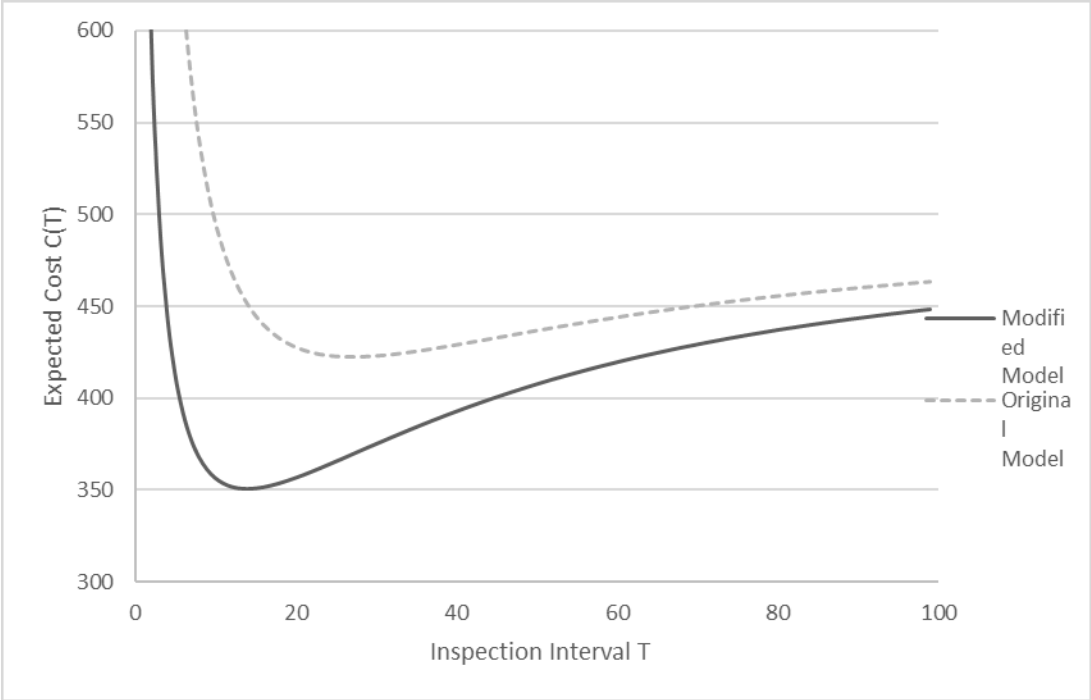

Figure 17: Comparison between original and modified expected total cost

The next table shows the total expected cost incurred at the specific inspection interval for each model.

Model	Inspection Interval	Total Expected Cost
Original Model	Every 24 hours	423.292
Modified Model	Every 35 hours	384.532

Table 17: Expected total cost summary

These numbers show that with the cost of breakdown, preventive maintenance, and inspection illustrated in the previous section the modified model has a lower total expected cost. The difference between the models show that the modified model has 38.76 units lower than the original base model. This is almost 9.16% lower in expected total cost.

3.5.2 Sensitivity Analysis

In order to validate the model a sensitivity analysis is carried out. The sensitivity analysis aims to study the effect of change to the results. One way to validate the model is to observe the behavior of the system as the variables change. The change in the analysis took place at the human factor H_f. In the first analysis the two extreme cases of the human factor are examined.

As the human factor H_f decreases the modified model should be closer to the original model. Meaning that the inspection time T should start decreasing to reach 24 hours as in the original model as well as the expected downtime D(T). On the other hand, as the

human factor H_f increases the inspection time T should increase. The following are the new inputs for the human factor for both extremes:

(a) Low Extreme Case: $H_f = 0.08$

- Experience: 5 years
- Fatigue: 0 reports
- Seriousness: Class 1

(b) High Extreme Case: $H_f = 0.92$

- Experience: 0 years
- Fatigue: 10 reports
- Seriousness: Class 4

The next two figures show the results of the expected downtime of the two extreme cases compared to the original model.

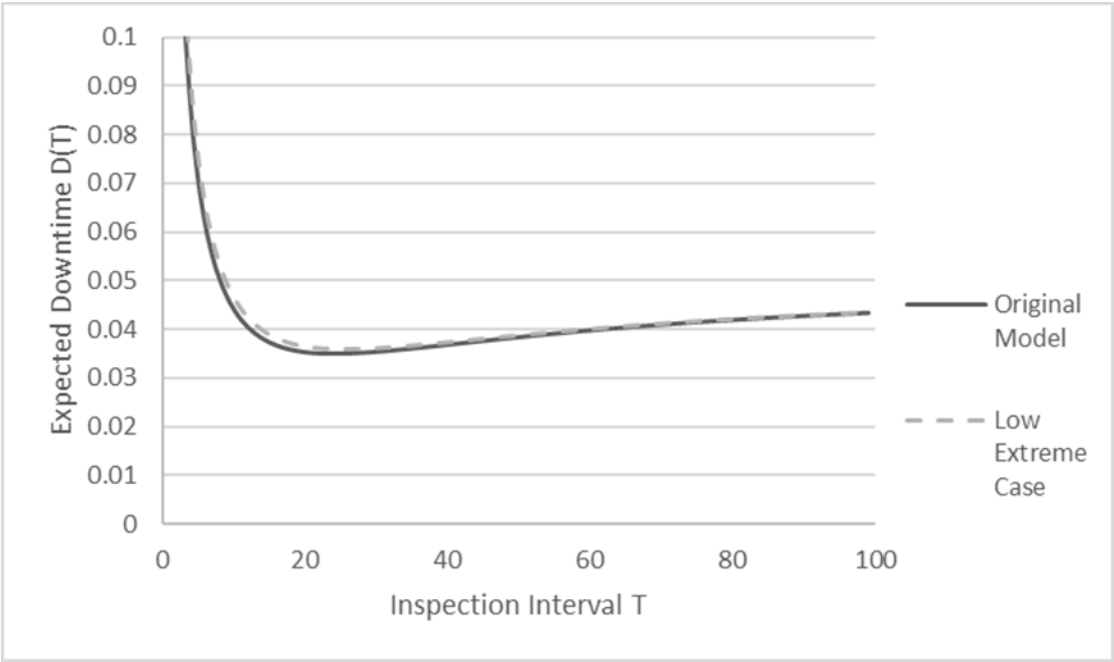

Figure 18: Low extreme case sensitivity analysis

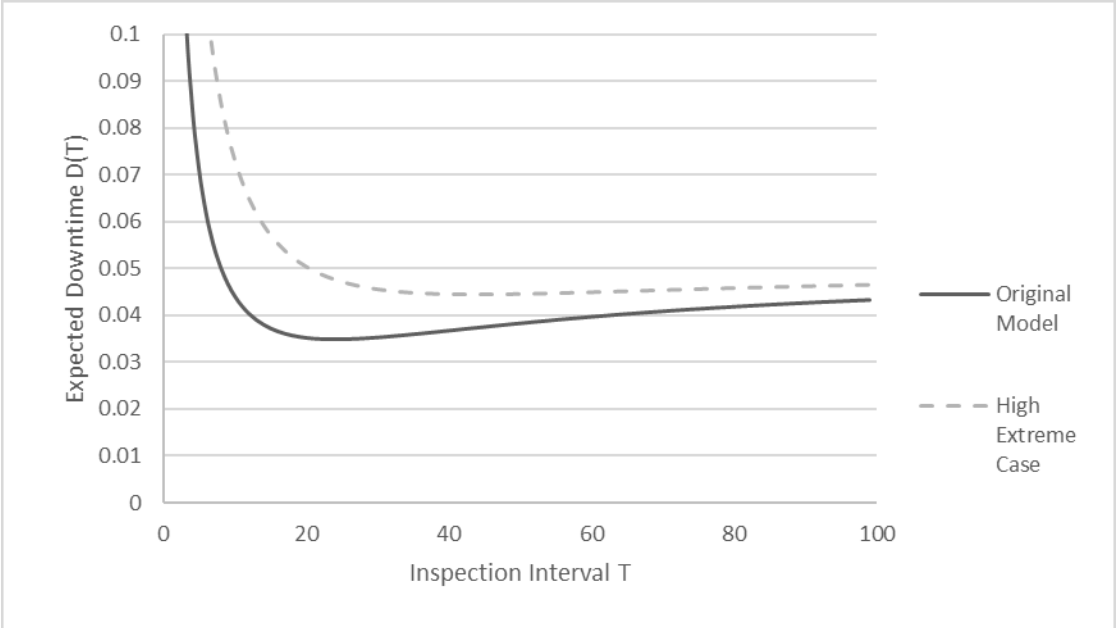

Figure 19: High extreme case sensitivity analysis

The results of the two figures are summarized in the next table.

Case	H_f	T	D(T)
Low Extreme	0.08	25	0.0360
High Extreme	0.92	44	0.0444
Original Case	0	24	0.0350

Table 18: Summary of low and high extreme cases

As shown in the table, as we decrease the human factor we move closer to the original model and vice versa. The difference between the expected downtime of the low extreme and the original model is almost 2.9% and this is due to the fuzzy logic inference system. The next sensitivity analysis is performed on different values of inputs and compared with the modified model to inspect the behavior of the results. The next figure shows the results of the sensitivity analysis:

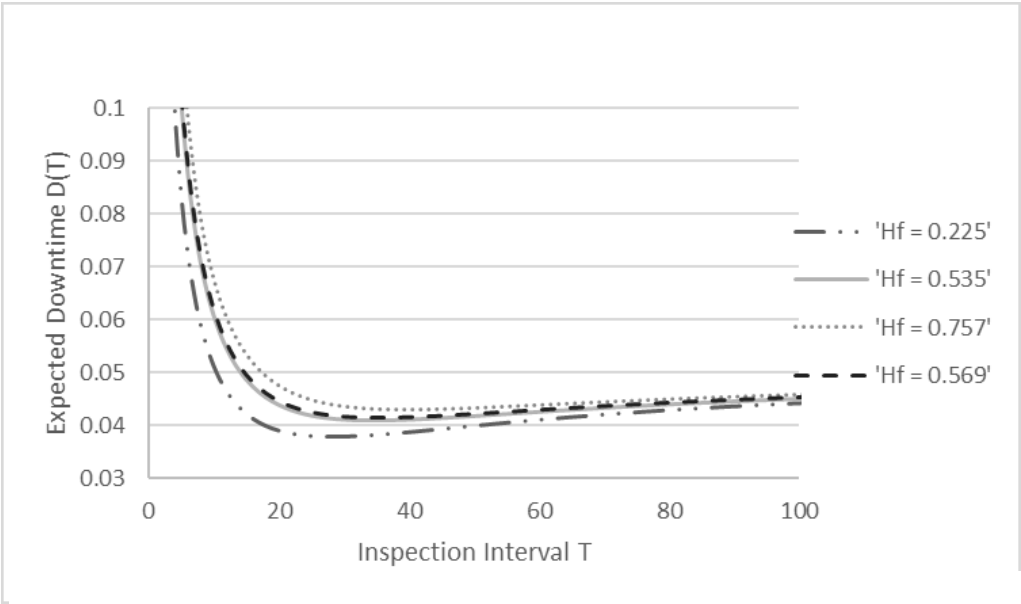

Figure 20: Sensitivity analysis of expected downtime vs. inspection interval T

The results from the figure are summarized in the next table.

Input	Hf	T	D(T)
Experience = 1 Fatigue = 4 Seriousness = 1	0.225	28	0.0378
Experience = 4.5 Fatigue = 8 Seriousness = 2	0.535	35	0.0411
Experience = 2 Fatigue = 2 Seriousness = 4	0.757	40	0.0431

Table 19: Summary of sensitivity analysis

The results show that as the human factor decreases the expected downtime and the inspection interval tend to decrease. This shows the same conclusion as in the two extreme cases.

CHAPTER 4

INTEGRATED SYSTEM OF DELAY TIME MODEL WITH HUMAN FACTORS IN INSPECTION TIME AND DELAY TIME

4.1 Introduction

Delay Time Modelling (DTM) as introduced in chapter 4 is defined as a two-stage model. The first stage starts when the defect becomes first detectible and the second stage is the period that the defect starts increasing till the failure occurs. The delay time is simply the period between the detection of the defect and the failure occurrence and is denoted by h. According to **(Wang 2012)** the delay time depends on four different inputs. These inputs affect how the delay time varies and when the failure occurs. In this chapter we will model the DTM by fuzzifying the delay time by taking into consideration the four

factors. In addition to the delay time, the inspection time used in the previous chapter is also injected into the model. In this chapter we will discuss the problem we are addressing first and then we will build the model incorporating the new delay time and the inspection time using the fuzzy logic. Next, we will solve an example and compare the results with the base model and perform validation on the model.

4.2 Problem Statement

The problem we are addressing in this chapter is similar to what was discussed in chapter 4. The difference between the two problems is that in the new problem the probability of faults becoming failures P(T) which depends on the delay time random variable h will be fuzzified. The fuzzification of this random variable depends on four inputs that affect the relationship of the delay time on the probability of faults breakdown. These four factors are the characteristic of item concerned, defect type, nature of inspection, and person performing the inspection. We will consider a single machine manufacturing system that processes a set of jobs. The machine in the system is subject to failure due to different factors which include; deterioration, design of machine, design of item, external factors, and maintenance activities. In this problem, faults arise in the machine and they are repaired as failure repairs or inspection repairs. The failure of the machine results in lost production and therefore results in production expected downtime D(T) and related costs that accumulate to the expected total cost C(T). Delay time analysis is used to model

the effects of the inspection policies on time period T. The probability of faults becoming failures or machine breakdowns P(T) increases as the inspection period T increases and is dependent on the four factors as will be explained in the next section.

The inspection activities are performed by maintenance operators, and inspection period varies depending on the operator performing the inspection task. The inspection performance in this problem is controlled by three factors; years of experience of operator, number of fatigue reports submitted by operator, and the seriousness level of the maintenance task. These three factors will contribute to the determination of the inspection period of the delay time model.

The problem that is being addressed here is to incorporate the human factors in modelling the inspection interval versus the production expected downtime and the expected total cost. The main objective is to minimize the total machine expected downtime and total expected cost by including the effect of humans during the inspection period and the human factors related to the delay time.

The approach in addressing the problem consists of building two fuzzy logic systems that will allow us to determine the Human Factors for the inspection time and to determine the delay time distribution, building the delay time model, integrating the output of the fuzzy system into the delay time model, applying a case study of the problem, and finally

comparing results of the delay time model with the integrated model. This approach is included in the next sections.

4.3 Model Development

In this section, the delay time model is developed to incorporate the human factors using the fuzzy logic system in determining the inspection downtime and the delay time. The main aim is to develop a model to determine the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' downtime. This section will include the development of the inspection downtime fuzzy logic system, expected downtime model, and the expected total cost model.

4.3.1 Delay Time h Fuzzy Logic System

In this section, a fuzzy logic model is designed and built to determine the delay time of the delay time model. The delay time h in the DTM model is a random variable and is modeled using a specific distribution f(h). The fuzzy logic will help in determining the distribution f(h) using four different inputs that will be discussed in detail in the next section. The four inputs are the characteristic of item concerned, defect type, nature of inspection, and person performing the inspection factor for the Inspection downtime in

the delay time model. The next three sub-sections explain the inputs' membership functions, outputs' membership functions, and the fuzzy rule base of the fuzzy logic system in details.

4.3.2 Delay Time Fuzzy Logic System

In this section, a fuzzy logic model is designed and built to determine the delay time in the DTM. The parameter that is fuzzified is the delay time to determine its distribution (this is explained in detail in the next chapter). The delay time is a random variable in the DTM and in most cases the distribution that is used is the exponential distribution to model it. Based on **(wang 2012)** in real life, delay time depends on four inputs which are: characteristics of item concerned, type of defect, nature of inspection, and person inspecting this parameter depends on many factors, in this model we will use these four factors as inputs to model the fuzzy logic system. The next two sections explain the inputs, fuzzy inference system and the output of the fuzzy logic system in details.

4.3.2.1 Establishing Membership Functions for the Inputs

As explained in the previous chapter the first step in building the fuzzy logic is determining the linguistic variables that will be used as inputs in the system. Based on Ung et al. (2009), the membership function to be used in such problems is the triangular membership function. This type of membership results in a smooth transition from one state to another and makes the deffuzification easier of the linguistic terms used in the model.

The linguistic term that is used to describe the first PSF is the Characteristic of the Item Concerned. This PSF is explained by **(Wang 2012)** as the ease of inspection of the item we are performing the maintenance activity on. The sets defining the characteristic of the item concerned are {Very Easy, Easy, Normal, Hard, Very Hard}. This set represents how easy or how hard is it to perform the inspection on the item. The interval for this input lies between 0 and 1 and is divided equally amongst the sets. The linguistic terms used for describing the characteristic of the item (CI) are as follows:

(a) CI1 – Very Easy
(b) CI2 – Easy
(c) CI3 – Normal
(d) CI4 – Hard
(e) CI5 – Very Hard

In order to model each of the characteristics of the item of the linguistic term in the triangular membership function, three parameters must be set. The parameters for each level are shown in the next table. A graphical representation of the characteristic of the item membership function is illustrated in the Figure below the table.

Ease of Inspection Level	Parameters		Function
CI1 – Very Easy	Minimum	0	Triangular {0, 0, 0.25}
	Mode	0	
	Maximum	0.25	
CI2 – Easy	Minimum	0	Triangular {0, 0.25, 0.5}
	Mode	0.25	
	Maximum	0.5	
CI3 – Normal	Minimum	0.25	Triangular {0.25, 0.5, 0.75}
	Mode	0.5	
	Maximum	0.75	
CI4 – Hard	Minimum	0.5	Triangular {0.5, 0.75, 1}
	Mode	0.75	
	Maximum	1	
CI5 – Very Hard	Minimum	0.75	Triangular {0.75, 1, 1}
	Mode	1	
	Maximum	1	

Table 20: Ease of Inspection Level Parameters

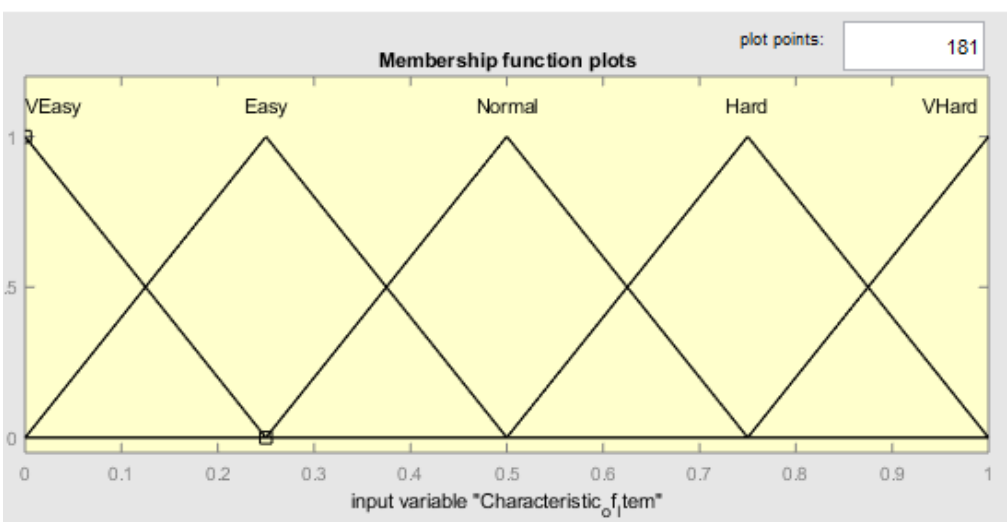

Figure 21: Characteristics of item membership function

The linguistic term that is used to describe the second PSF is the Type of defect of the item. This is explained as the criticality level of the defect of the item on the system. The sets defining the type of defect are {No Criticality, Low Criticality, Regular Criticality, Critical, Highly Critical}. This set represents the level of criticality and how serious the defect is on the system. The interval for this input lies between 0 and 1 and is divided equally amongst the sets. The linguistic terms used for describing the type of defect criticality level (D) are as follows:

(a) D1 – No Criticality
(b) D2 – Low Criticality
(c) D3 – Regular Criticality
(d) D4 – Critical
(e) D5 – Highly Critical

In order to model each of the type of defect of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next table. A graphical representation of the type of defect membership function is illustrated in the Figure below the table.

Criticality Level	Parameters		Function
CI1 – No Criticality	Minimum	0	Triangular {0, 0, 0.25}
	Mode	0	
	Maximum	0.25	
CI2 – Low Criticality	Minimum	0	Triangular {0, 0.25, 0.5}
	Mode	0.25	
	Maximum	0.5	
CI3 – Regular Criticality	Minimum	0.25	Triangular {0.25, 0.5, 0.75}
	Mode	0.5	
	Maximum	0.75	
CI4 – Critical	Minimum	0.5	Triangular {0.5, 0.75, 1}
	Mode	0.75	
	Maximum	1	
CI5 – Highly Critical	Minimum	0.75	Triangular {0.75, 1, 1}
	Mode	1	
	Maximum	1	

Table 21: Criticality Level Parameters

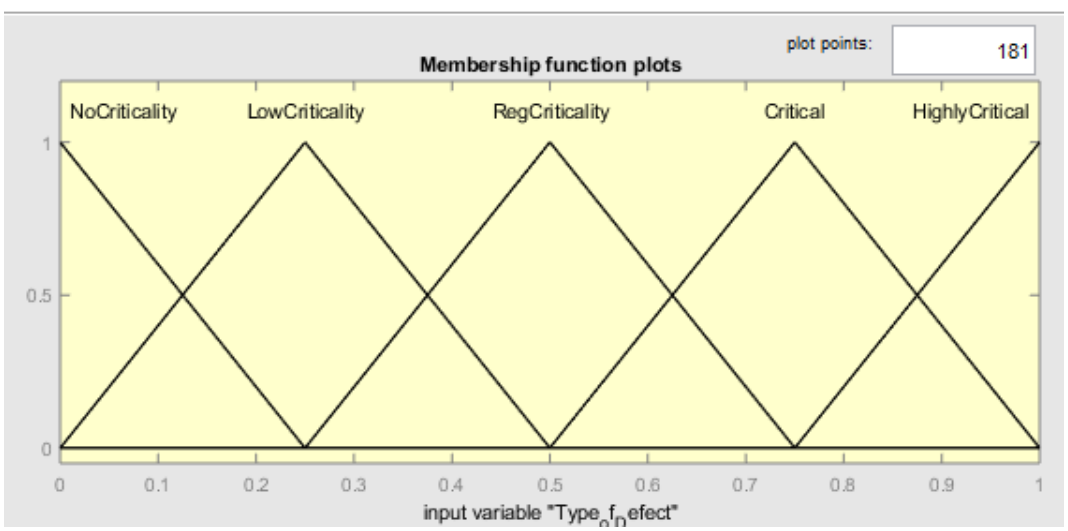

Figure 22: Type of defect membership functions

The linguistic term that is used to describe the third PSF that will be used in this fuzzy system is the nature of inspection performed in terms of the adequacy of obtaining information of the item inspected. The sets defining the nature of inspection are {Low, Medium, High}. This set represents the class the adequacy of obtaining data and information of item. The interval is set based on applications in the literature as presented by **Sergaki and Kalaitzakis (2002).** The linguistic terms used for describing the adequacy (I) are as follows:

(a) I1 – Low
(b) I2 – Medium
(c) I3 – High

To model each of the adequacy levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The adequacy level is a subjective matter, but it's usually determined by experts. A graphical representation of the adequacy level membership function is illustrated in the Figure below the table.

Adequacy Level	Parameters		Function
I1 – Low	Minimum	0	Triangular {0, 0, 0.5}
	Mode	0	
	Maximum	0.5	
I2 – Medium	Minimum	0	Triangular {0, 0.5, 1}
	Mode	0.5	
	Maximum	1	
I3 – High	Minimum	0.5	Triangular {0.5, 1, 1}
	Mode	1	
	Maximum	1	

Table 22: Adequacy Levels Parameters

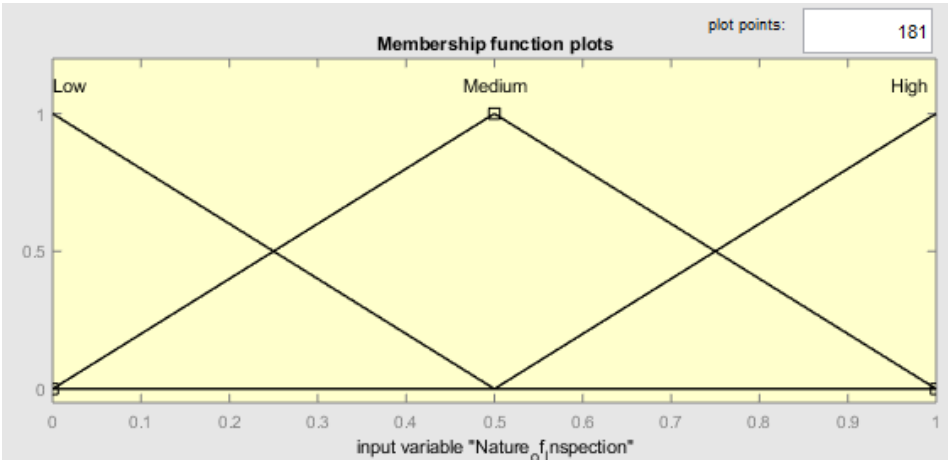

Figure 23: Nature of inspection membership function

The linguistic term that is used to describe the last PSF is the Person Inspecting the item which can be expressed as the Experience of the worker performing the maintenance activity. The sets defining the experience of the worker are {Low, Medium, High}. This set represents the number of years of experience the worker has in the maintenance field. The interval of the experience of the worker is between 0 and 5 years of experience. The

interval is set based on applications in the literature **Hennequin and Arango (2009),** experts that have worked in the maintenance in the manufacturing industry, and research done in different job hunting sites. The linguistic terms used for describing the experience of the worker (E) are as follows:

(a) E1 – Low
(b) E2 – Medium
(c) E3 – High

In order to model each of the experience levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next table. A graphical representation of the experience of workers membership function is illustrated in the Figure below the table.

Experience Level	Parameters		Function
E1 – Low	Minimum	0	Triangular {0, 0, 2.5}
	Mode	0	
	Maximum	2.5	
E2 – Medium	Minimum	0	Triangular {0, 2.5, 5}
	Mode	2.5	
	Maximum	5	
E3 – High	Minimum	2.5	Triangular {2.5, 5, 5}
	Mode	5	
	Maximum	5	

Table 23: Experience Level Parameters

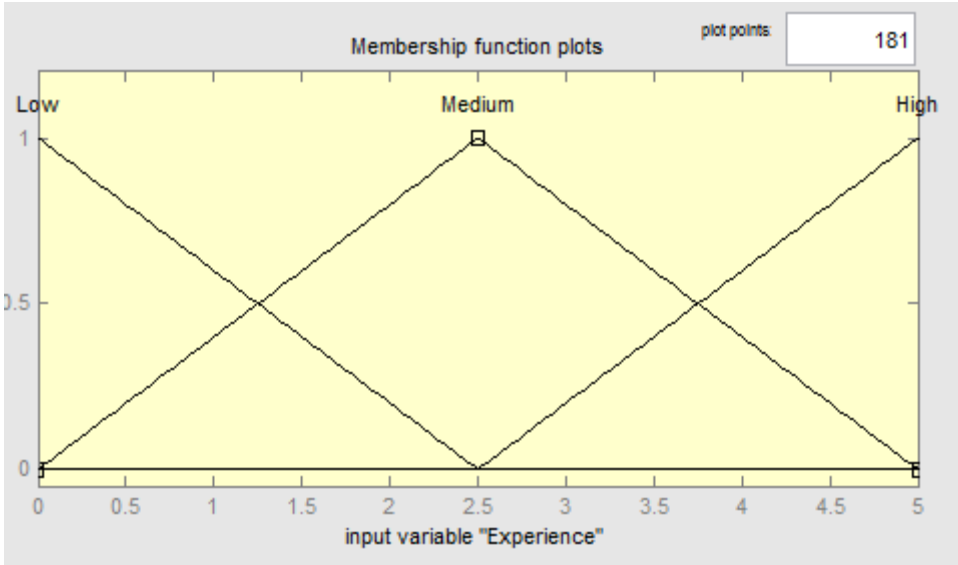

Figure 24: Experience level membership function

Now that all the input linguistic terms have been defined along with their parameters, the output of the fuzzy model is to be defined in the next section.

4.3.2.2 Establishing Membership Functions for the Outputs

The output in our case is the consequence of all the inputs put together. In other words, how will the four-performance shaping factors that we are using affect the model. We will look at the output in terms of delay time which will be explained in detail in the next sections. The output is defined as the delay time of the item depending on the characteristic of the items, type of defect, nature of inspection, and person inspecting and performing the maintenance task. The linguistic term that is used to describe the output of the fuzzy logic system is Delay Time. This factor has a range from 0 to 100 and will be used as an input in the delay time modelling presented in the next chapter. The sets

defining the human factor are {Very Low, Low, Medium, High, Very High}. These sets are used as follows to describe the human factor (HF):

(a) DT1 – Very Low
(b) DT2 – Low
(c) DT3 – Medium
(d) DT4 – High
(e) DT5 – Very High

Delay Time Level	Parameters		Function
DT1 – Very Low	Minimum	0	Triangular {0, 0, 25}
	Mode	0	
	Maximum	25	
DT2 – Low	Minimum	0	Triangular {0, 25, 50}
	Mode	25	
	Maximum	50	
DT3 – Medium	Minimum	25	Triangular {25, 50, 75}
	Mode	50	
	Maximum	75	
DT4 – High	Minimum	50	Triangular {50, 75, 100}
	Mode	75	
	Maximum	100	
DT5 – Very High	Minimum	75	Triangular {75, 100, 100}
	Mode	100	
	Maximum	100	

Table 24: Delay Time Levels Parameters

To model each of the human factor levels of the linguistic term in the triangular membership function, three parameters must be set. These parameters are {Minimum, Mode, Maximum}. The parameters for each level are shown in the next Table. These parameters are subjective and based on different applications from the literature and can

be altered depending on the specific problem addressed. A graphical representation of the fatigue of workers membership function is illustrated in the Figure below the table.

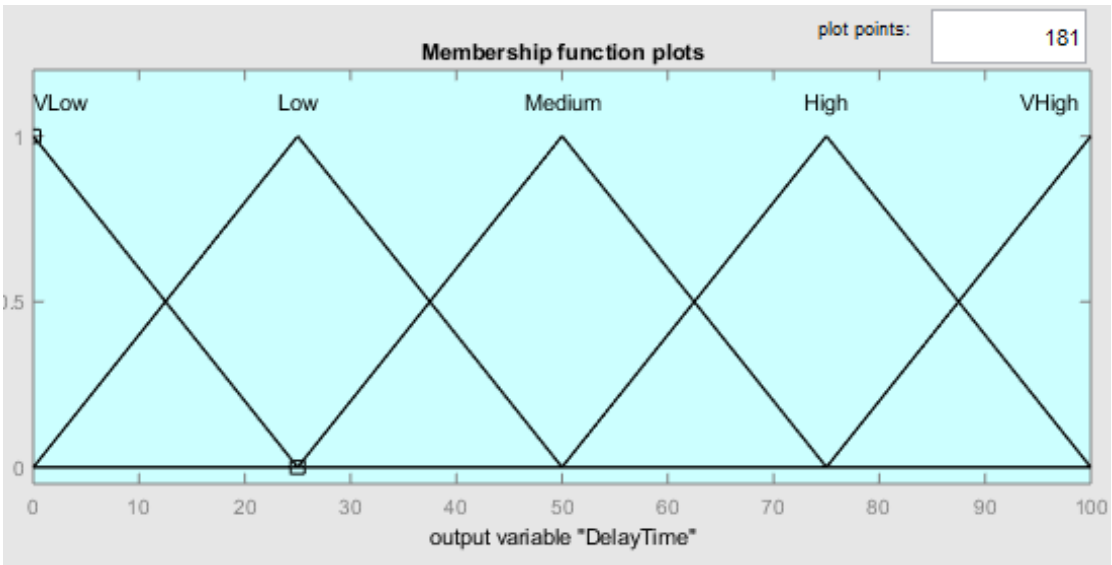

Figure 25: Delay Time Membership functions

The next figure summarizes all the inputs and output with their defined sets.

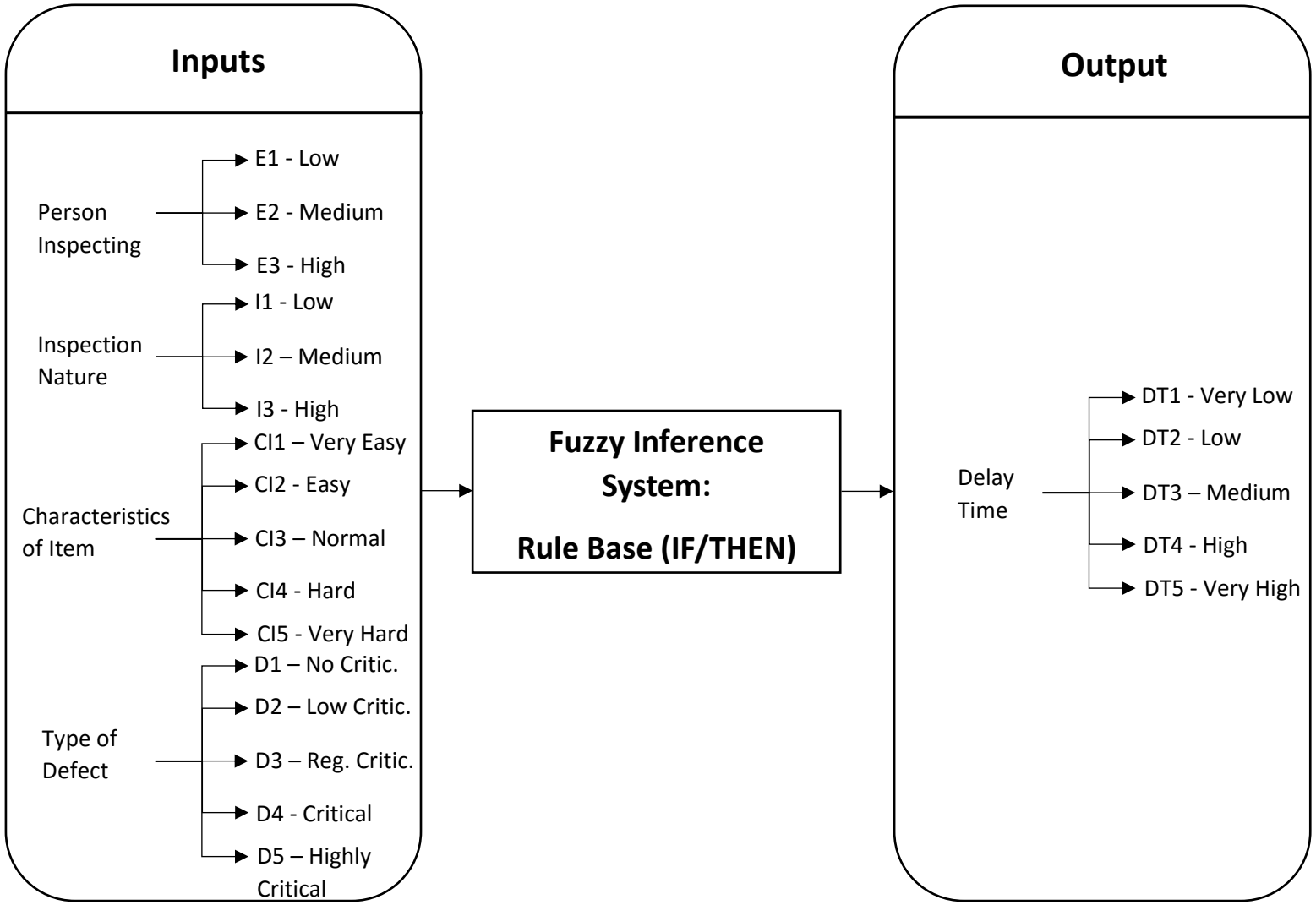

Figure 26: Delay Time Fuzzy System Summary

4.3.3 Developing a Fuzzy Rule Base

A fuzzy rule base as explained in the previous chapter is a system that is built in the form of IF/THEN rules. The IF part are the input variables that are defined in the previous section (Characteristics of Item, Type of Defect, Inspection Nature, and Person Inspecting). The THEN part is the output variable that is defined earlier (Delay Time). The fuzzy rule base developed, given the level of ease of inspection, the criticality level, the adequacy level, and the years of experience, assigns a delay time to the job (DT). An example of this is, IF ease of inspection CI3 is normal and the criticality level is highly critical D5 and the adequacy level is low I1 and finally the worker's experience is medium E2 THEN Delay Time DT4 high is established given the results. This will help us to determine which distribution to use in the model.

The number of rules that the system has is the product of all the possible combinations of sets of the linguistic variables. In this case the number of rules to be developed is determined as follows:

Ease of Inspection {5} Criticality {3} Adequacy {3} Experience {3}

Number of Rules = 5 x 5 x 3 x 3 =225 Rules

The evaluation and development of rules are based on probabilities. Each level in the inputs is given a probability. The probabilities of the inputs are divided equally amongst the levels of each input. The next table shows the input and output levels with their corresponding probabilities that are used to develop the rules.

Number	PSF	Levels of PSF				
		Input				
1	Characteristic of Item Concerned	Very Easy	Easy	Normal	Hard	Very Hard
	Cumulative Probability of Levels	0.20	0.40	0.60	0.80	1.00
2	Type of Defect	No Criticality	Low Criticality	Regular Criticality	Critical	Highly Critical
	Cumulative Probability of Levels	0.20	0.40	0.60	0.80	1.00
3	Nature of Inspection	High		Medium		Low
	Cumulative Probability of Levels	0.33		0.67		1.00
4	Person Inspecting	High		Medium		Low
	Cumulative Probability of Levels	0.33		0.67		1.00
		Output				
5	Delay Time	Very Low	Low	Medium	High	Very High
	Cumulative Probability of Levels	0.20	0.40	0.60	0.80	1.00

Table 25: Summary of Inputs and Output

The method for setting the rules is divided into two steps as follows:

a) Taking the average of the inputs

The first step in obtaining the rules is by taking the average of all the cumulative probabilities of the corresponding inputs. In this case we assume that the inputs have the same weight and contribute equally on the system when performing the average and the rules.

b) Determining to which level of output the inputs correspond to

After determining the average of the combinations, the next step is to decide to which level of output it belongs to. The averages hold values between 0.2 as the minimum and 1 as the maximum. The difference between the maximum and minimum is divided equally

between the five levels of the output delay time. The next table shows the levels of outputs with their corresponding ranges.

Level	Range
Very Low	[0.2 - 0.36)
Low	[0.36 - 0.52)
Medium	[0.52 - 0.68)
High	[0.68 - 0.84)
Very High	[0.84 - 1]

Table 26: Output Ranges

The following example shows how the rules are developed.

Example

Ease of Inspection = CI3 Adequacy = I2 Criticality=D5 Experience=E1

Corresponding Probabilities:

CI3=0.6 I2=0.67 D5=1.0 E1=0.33

Their average:

$$Average = \frac{0.6 + 0.67 + 1 + 0.33}{4} = \frac{2.6}{4} = 0.65$$

If we look at the previous table, this average fall in the range of the **medium** delay time. All the rules are developed similar to the example and the all the rules are included in appendix A. The next table shows a sample of the rules developed.

IF									THEN	
Concerned Item	Pr	Criticality	Pr	Adequacy	Pr	Experience	Pr		Output	Pr
Very Easy	0.20	No Criticality	0.20	Low	1.00	Low	1.00		Medium	0.60
Very Easy	0.20	No Criticality	0.20	Low	1.00	Medium	0.67		Low	0.52
Very Easy	0.20	No Criticality	0.20	Low	1.00	High	0.33		Low	0.43
Very Easy	0.20	No Criticality	0.20	Medium	0.67	Low	1.00		Low	0.52
Very Easy	0.20	No Criticality	0.20	Medium	0.67	Medium	0.67		Low	0.43
Very Easy	0.20	No Criticality	0.20	Medium	0.67	High	0.33		Very Low	0.35
Very Easy	0.20	No Criticality	0.20	High	0.33	Low	1.00		Low	0.43
Very Easy	0.20	No Criticality	0.20	High	0.33	Medium	0.67		Very Low	0.35
Very Easy	0.20	No Criticality	0.20	High	0.33	High	0.33		Very Low	0.27
Very Easy	0.20	Low Criticality	0.40	Low	1.00	Low	1.00		Medium	0.65
Very Easy	0.20	Low Criticality	0.40	Low	1.00	Medium	0.67		Medium	0.57
Very Easy	0.20	Low Criticality	0.40	Low	1.00	High	0.33		Low	0.48
Very Easy	0.20	Low Criticality	0.40	Medium	0.67	Low	1.00		Medium	0.57

Table 27: Sample of rules

4.3.4 Expected Downtime Model Development

In this section, the delay time model is developed to incorporate the output of the fuzzy system presented in the previous section of obtaining the delay time and the previous chapter in obtaining the inspection time. The main aim is to develop a model that predicts the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' downtime. The objective for this model is to minimize the expected downtime.

In this model we will incorporate the inputs of the delay time discussed in the previous section to build the delay time model. The probability density function of the delay time

in this model will be built depending on the output of the fuzzy model built in the previous section. The notations that are used in this model are presented in the following table.

T	Inspection period
$FP(T)$	Fuzzy probability of defects detected rises to breakdown
$FD(T)$	Fuzzy expected downtime of system per unit time
k	Arrival rate of defects per unit time
d	Time needed to perform the inspection
H_f	Human factor associated with time of inspection
h_{fuzzy}	Delay time (time between fault arise and time of failure) using fuzzy logic system
$f(h_{fuzzy})$	Probability density function of delay time based on the fuzzy logic system
d_b	Average downtime for breakdown repair

Table 28: Notations 3 table

Now that the notations have been defined, the assumptions of the model are as follows:

a- Inspection action takes place every T time units and needs $(1+H_f)d$ time units. d is smaller than T $(d<<T)$.

b- Perfect inspection actions take place, meaning all defects and faults are recognized in the inspection action

c- The delay time *h* is independent from the defect arrival time and its density function *f(h)* is based on the fuzzy system output

d- Defect and failures arrivals follow a homogeneous Poisson distribution and they arise at a rate of *k* per unit time

e- Defects identified are repaired in the inspection period, assuming maintenance operators are enough and available at all times.

f- H_f is the human factor from the operator performing the inspection task and depends on the experience, fatigue and seriousness of task.

The delay time process is shown in the next Figure. The fault arising is repaired as a breakdown repair if it occurs in the interval (*0, T-h*), otherwise as an inspection repair if it occurs in the interval (*T-h, T*). The inspection occurs every *T* time units and the faults arise in the interval (*0, T*). The faults have a delay time in the interval (*h, h+dh*). And the probability of this happening is given by *f(h)dh*

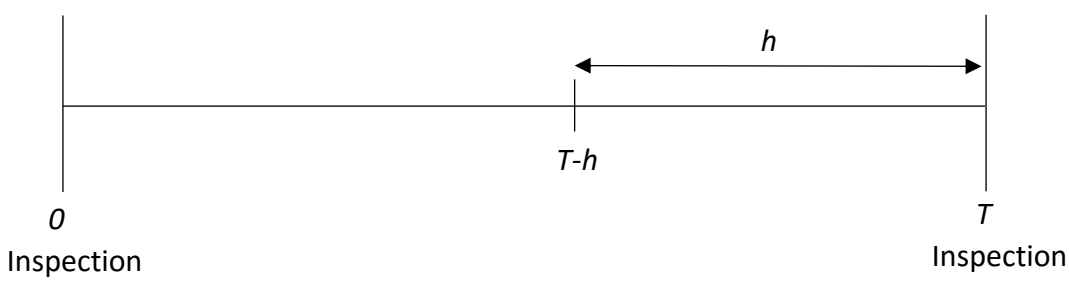

Figure 27: Delay Time Process

Assumption (e) states that all the repairs that are needed during the inspection are performed and finished within the given inspection period. Since the number of maintenance operators are enough, no matter how many repairs are to be performed it

can be done if the operators work on the repairs simultaneously. The expected number of failures during the period *T* is given by:

$$Expected\ number\ of\ failures$$
$$= Arrival\ rate\ of\ defects\ per\ unit\ time * Time\ interval$$

$$Expected\ number\ of\ failures = kT$$

The expected number of failures is only when the machine is busy, therefore ignores the downtime due to breakdowns where there are no defects or faults occurring when the machine is idle.

The probability that a fault is repaired as a breakdown means that it occurs before *T-h* and this is described as:

$$probability\ of\ fault\ arising\ before\ T - h = \frac{T - h}{T}$$

This probability that the fault has a breakdown and has the delay time in (*h, h+dh)* is

$$\left(\frac{T - h}{T}\right) f(h)dh$$

The probability density function f(h) that is used in this model is determined using the output of the fuzzy logic system. The output of the fuzzy model in the previous section is shown as multiple triangular distributions. f(h) is described as:

$$f(h) \begin{cases} 0 & for\ h < a \\ \dfrac{2(h-a)}{(b-a)(c-a)} & for\ a \leq h < c \\ \dfrac{2}{(b-a)} & for\ h = c \\ \dfrac{2(b-h)}{(b-a)(b-c)} & for\ c < h \leq b \\ 0 & for\ b < h \end{cases}$$

where these a, b, and c are the parameters of the triangular distribution as shown in the following figure.

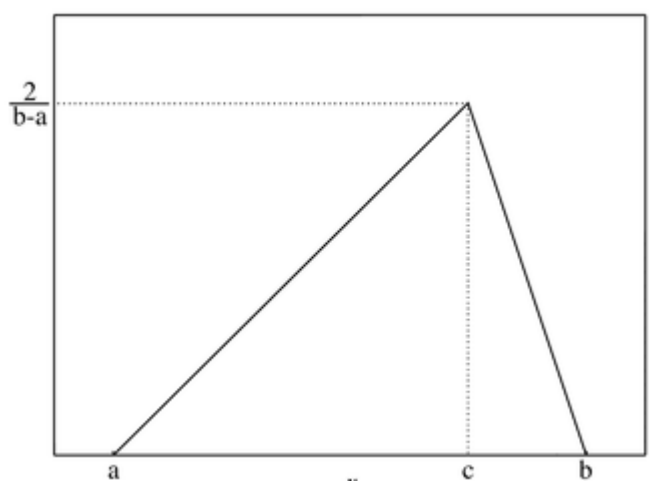

Figure 28: Triangular Distribution Parameters

Taking the probability over all values of h, it is given by

$$FP(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f(h)dh$$

The expected downtime for breakdowns and inspection is given described as

$$Expected\ downtime = kTd_b FP(T) + (1 + H_f)d$$

Then the expected downtime per unit time to be incurred in period *T* is *D(T)* where

$$FD(T) = \frac{kTd_b FP(T) + (1 + H_f)d}{T + (1 + H_f)d}$$

4.3.5 Expected Total Cost Model Development

In this section, the delay time model is developed to incorporate the output of the fuzzy system presented in the previous section of obtaining the delay time and the previous chapter in obtaining the inspection time. The main aim is to develop a model that predicts the optimal value for the inspection period and allows the prediction of the consequences of the period change on the systems' cost. The objective for this model is to minimize the total expected cost.

In this model we will incorporate the inputs of the delay time discussed in the previous section to build the delay time model. The probability density function of the delay time

in this model will be built depending on the output of the fuzzy model built in the previous section. The notations that are used in this model are presented in the following table.

T	Inspection period
$FP(T)$	Probability of defects detected rises to breakdown
k	Arrival rate of defects per unit time
d	Minimum time needed to perform the inspection
H_f	Human factor associated with time of inspection
h_{fuzzy}	Delay time (time between fault arise and time of failure) using fuzzy logic system
$f(h_{fuzzy})$	Probability density function of delay time based on the fuzzy logic system
C_b	Cost of breakdown repair
$FC_b(T)$	Fuzzy expected cost of breakdown repair
C_{pm}	Preventive maintenance action cost
$FC_{pm}(T)$	Fuzzy expected preventive maintenance cost
C_i	Maximum cost that is needed to perform the inspection
$FC(T)$	Fuzzy expected total cost per unit time

Table 29: Notations 4 table

Now that the notations have been defined, the assumptions of the model are similar to the assumptions presented in the previous section as both models are the same and only the objective function differs. One assumption to emphasize on is that the cost of breakdown is higher than cost of preventive maintenance. The development of the model is as follows.

The expected number of failures during the period *T* is given by:

$$Expected\ number\ of\ failures$$
$$= Arrival\ rate\ of\ defects\ per\ unit\ time * Time\ interval$$

$$Expected\ number\ of\ failures = kT$$

The expected number of failures is only when the machine is busy, therefore ignores the downtime due to breakdowns where there are no defects or faults occurring when the machine is idle.

The probability that a fault is repaired as a breakdown means that it occurs before *T-h* and this is described as:

$$probability\ of\ fault\ arising\ before\ T - h = \frac{T - h}{T}$$

This probability that the fault has a breakdown and has the delay time in (*h, h+dh)* is

$$\left(\frac{T - h}{T}\right) f(h)dh$$

The probability density function f(h) that is used in this model is determined using the output of the fuzzy logic system. The output of the fuzzy model in the previous section is shown as multiple triangular distributions. f(h) is described as:

$$f(h) \begin{cases} 0 & for\ h < a \\ \dfrac{2(h-a)}{(b-a)(c-a)} & for\ a \leq h < c \\ \dfrac{2}{(b-a)} & for\ h = c \\ \dfrac{2(b-h)}{(b-a)(b-c)} & for\ c < h \leq b \\ 0 & for\ b < h \end{cases}$$

where these a, b, and c are the parameters of the triangular distribution as shown in the following figure.

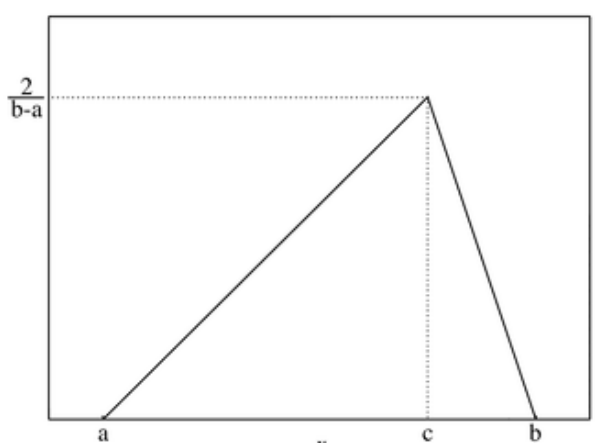

Figure 29: Triangular Distribution

Taking the probability over all values of h, it is given by

$$FP(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f(h)dh$$

In order to obtain the fuzzy expected total cost, three costs are incurred in the model and they are:

$$\begin{aligned} &Fuzzy\ expected\ total\ cost \\ &\qquad = Fuzzy\ expected\ breakdown\ repair\ cost \\ &\qquad + Fuzzy\ expected\ preventive\ maintenance\ cost \\ &\qquad + Inspection\ cost \end{aligned}$$

Where the fuzzy expected breakdown repair cost denoted by $FC_b(T)$ is given by:

$$\begin{aligned} &E\text{xpected breakdown repair cost} \\ &\qquad = Breakdown\ repair\ cost * Expected\ number\ of\ breakdowns \end{aligned}$$

$$FC_b(T) = C_b kTFP(T)$$

Similarly, the fuzzy expected cost of preventive maintenance denoted by $FC_{pm}(T)$ is given by

$$FC_{pm}(\mathrm{T}) = C_{pm} kT(1 - FP(T))$$

The last element of the total cost is the inspection cost. The inspection cost C_i is assumed to be the ideal cost where an expert with no fatigue and the seriousness of the task is low and this would result in the highest cost of all combinations. Adding the human factor into the inspection cost will result in the following expected total cost F*C(T):*

$$FC(T) = \frac{C_b kT * FP(T) + C_{pm} kT\big(1 - FP(T)\big) + (1 - H_f)C_i}{T + (1 + H_f)d}$$

4.4 Numerical Example and Results

In this section, a descriptive illustration for the model developed earlier is shown using the data from the literature (**Carr and Christer**, **2003**). For the human factor (H_f) and the delay time (h_{fuzzy}) with its distribution ($f(h_{fuzzy})$), they are obtained using the fuzzy inference system described earlier. The fuzzy inference systems are solved using MATLAB program.

Consider a manufacturing system with one machine that is subject to breakdowns. The machine has the following breakdown and failure parameters: the probability density function of the delay time follows a distribution based on the output of the fuzzy inference system. In this example the distribution that is used is the triangular distribution. The probability density function of the delay time is given as:

$$f(h) \begin{cases} 0 & for\ h < a \\ \dfrac{2(h-a)}{(b-a)(c-a)} & for\ a \leq h < c \\ \dfrac{2}{(b-a)} & for\ h = c \\ \dfrac{2(b-h)}{(b-a)(b-c)} & for\ c < h \leq b \\ 0 & for\ b < h \end{cases}$$

The output of the fuzzy logic system shows multiple triangular distributions. we will use the distribution that fits the model as will be shown later.

The breakdown downtime $d_b = 0.5$ hours and the inspection downtime $d = 0.35$ hours. The arrival rate of defects $k = 0.1$ defects per hour. Assume that the maintenance operator performing the inspection and maintenance has *3 years* of experience, he reported *2 fatigue reports* during the day, and the top management classify the machine's seriousness as *Class 3*. The inputs of the delay time are as follows: x the operator performing the inspection has half a year of experience, the criticality level of the machine 0.277, the adequacy level is 0.560, and the ease of inspection is 0.378 These parameters are used to determine the *T* that minimizes the expected total downtime *D(T).*

The first step in determining the expected total downtime, the human factor H_f is to be determined using the information given.

- Experience = 3 years
- Fatigue = 6 reports
- Seriousness = Class 3

These three parameters were used in the example in the previous chapter and the output of the system gives a value of 0.569 for the human factor H_f.

The next step is to determine the delay time probability distribution based on the four factors associated with it. The values that will be used to determine the distribution are:

- Ease of inspection = 37.8%
- Criticality = 27.7%
- Adequacy = 56%
- Experience = 0.5 years

Figure 30: Fuzzy logic inputs

Running the fuzzy logic system with the specified inputs result in a delay time DT value of 29.9 hours and this output from the system is shown in the figure in the next page.

The next step is to determine which triangular distribution to use based on the inputs. The next figure shows the output distribution of the delay time. Making a vertical line at the value of the output of the fuzzy logic system (29.9) intersects two distribution functions.

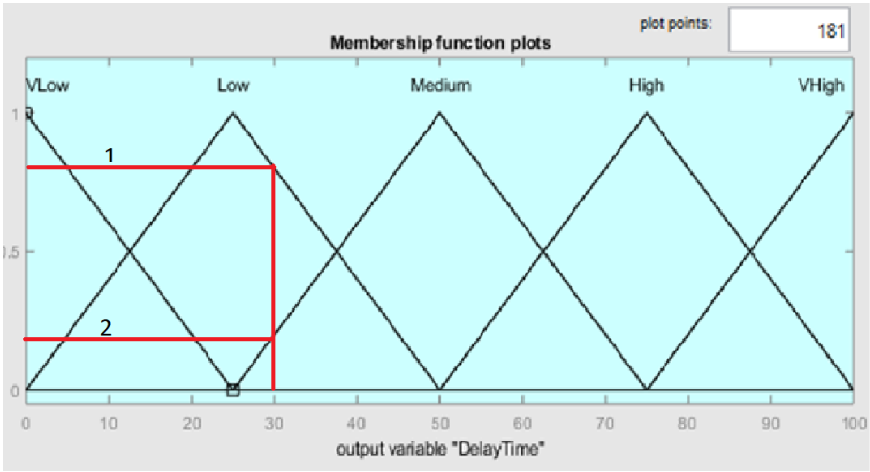

Figure 31: Output distribution of delay time

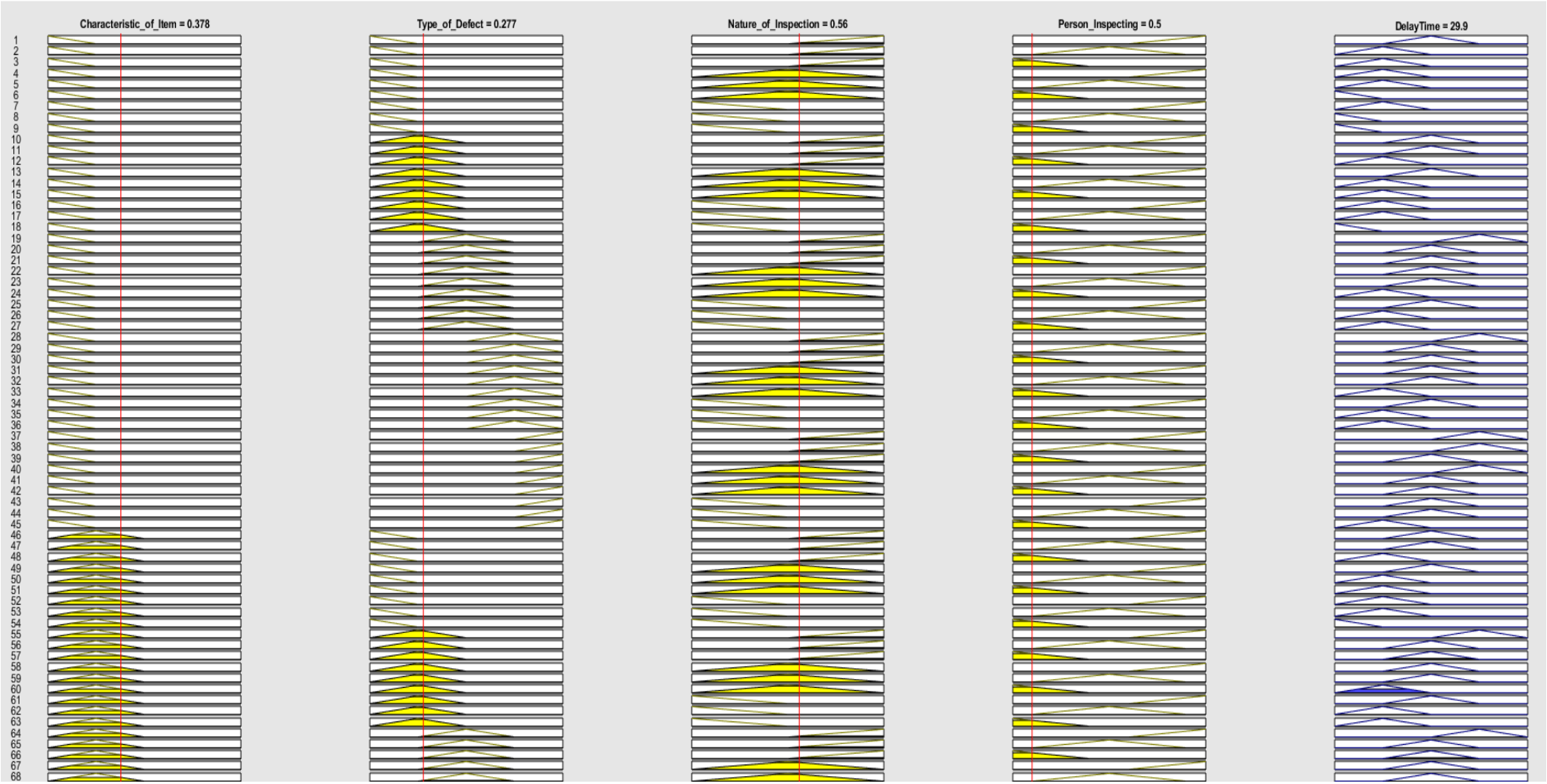

Figure 32: Fuzzy Logic II Output Results

This means that the triangular distribution number 1 contributes with 80% and the triangular distribution number 2 contributes with 20% to the system. Another interpretation would be 80% of the time triangular distribution number 1 is applied and 20% triangular distribution number 2 is used. In our case we will use a combination of the distributions based on their contributions to the system.

Next step, is to implement the results of the fuzzy logic system into the delay time model along with the other parameters. These results will form the expected breakdown downtime per unit time of:

$$D(T) = \frac{kTd_bP(T) + (1 + T_f)d}{T + (1 + H_f)d}$$

$$D(T) = \frac{0.1 * T * 0.5 * P(T) + (1 + 0.569) * 0.35}{T + (1 + 0.569) * 0.35} = \frac{0.05 * TP(T) + 0.5492}{T + 0.5492}$$

The probability that a fault has a breakdown *P(T)* is obtained using:

$$P(T) = 0.8 * \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f1(h)dh + 0.2 * \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f2(h)dh$$

Where *f1(h)* and *f2(h)* are as follows:

$$f1(h) \begin{cases} 0 & for\ h < 0 \\ \dfrac{2(h-0)}{(50-0)(25-0)} & for\ 0 \le h < 25 \\ \dfrac{2}{(50-0)} & for\ h = 25 \\ \dfrac{2(50-h)}{(50-0)(50-25)} & for\ 25 < h \le 50 \\ 0 & for\ 50 < h \end{cases}$$

$$f2(h) \begin{cases} 0 & for\ h < 25 \\ \dfrac{2(h-25)}{(75-25)(50-25)} & for\ 25 \le h < 50 \\ \dfrac{2}{(75-25)} & for\ h = 50 \\ \dfrac{2(75-h)}{(75-25)(75-50)} & for\ 50 < h \le 75 \\ 0 & for\ 75 < h \end{cases}$$

The method of obtaining the time interval *T* that minimizes the expected downtime of system is using searching technique through numerical analysis. The table below shows the values of *T* and their corresponding *D(T).*

T	D(T)	T	D(T)	T	D(T)
1	0.25926716	34	0.021998098	67	0.032685454
2	0.148972482	35	0.022310231	68	0.032932182
3	0.104563582	36	0.022636002	69	0.03317341
4	0.080616705	37	0.022973028	70	0.033409145
5	0.065669782	38	0.023319183	71	0.033639391
6	0.055480945	39	0.023672545	72	0.033864161
7	0.048116825	40	0.024031392	73	0.03408346
8	0.04257022	41	0.024394163	74	0.034297279
9	0.038264813	42	0.024759445	75	0.03450564
10	0.034847021	43	0.025125967	76	0.034708579
11	0.032087871	44	0.025492551	77	0.03490627
12	0.029832551	45	0.02585814	78	0.035098915
13	0.027972634	46	0.026221762	79	0.035286705
14	0.026429919	47	0.026582525	80	0.03546982
15	0.02514658	48	0.026939621	81	0.035648464
16	0.02407894	49	0.027292293	82	0.035822708
17	0.023193391	50	0.027639854	83	0.035992801
18	0.022463651	51	0.027981769	84	0.036158857
19	0.021868872	52	0.02831796	85	0.036321031
20	0.021392301	53	0.028648448	86	0.036479447
21	0.021020328	54	0.028973251	87	0.03663423
22	0.020741775	55	0.029292381	88	0.036785512
23	0.02054738	56	0.029605869	89	0.036933408
24	0.020429405	57	0.029913726	90	0.037078028
25	0.020381328	58	0.030215961	91	0.037219486
26	0.020396911	59	0.030512598	92	0.037357878
27	0.020468102	60	0.030803645	93	0.037493307
28	0.020587325	61	0.031089119	94	0.037625865
29	0.020748029	62	0.031369022	95	0.037755635
30	0.020944536	63	0.031643378	96	0.037882719
31	0.021171886	64	0.031912189	97	0.03800719
32	0.021425739	65	0.032175465	98	0.038129131
33	0.021702269	66	0.032433218	99	0.038248616

Table 30: Expected downtime with respect to time interval T

After obtaining the expected downtime for each inspection period, the inspection period is plotted against the expected downtime. The next figure illustrates the results.

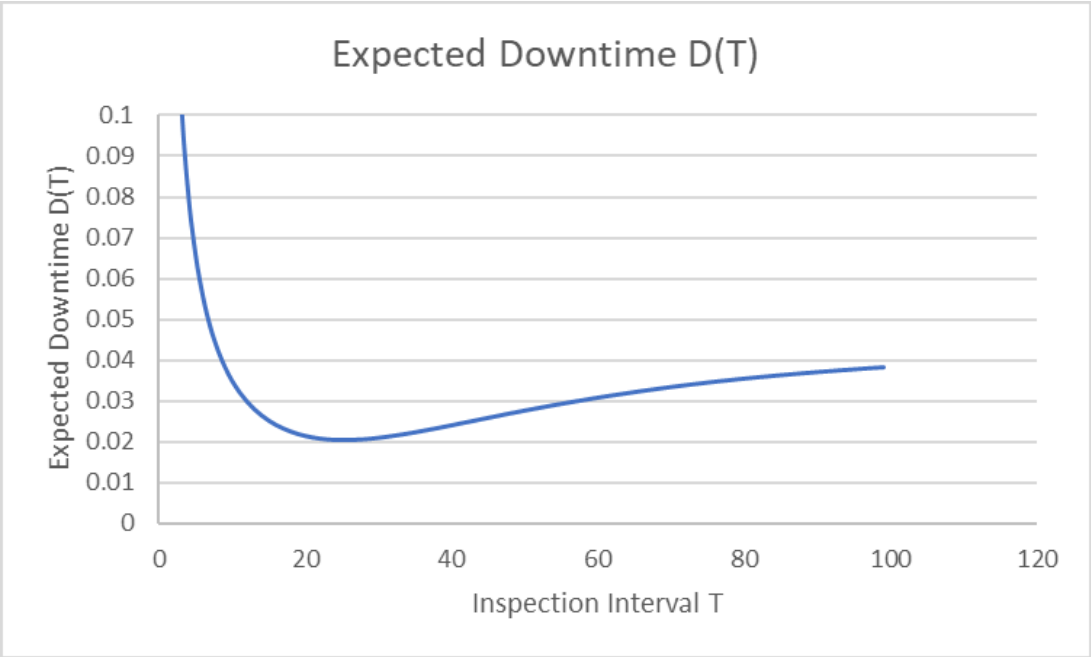

Figure 33: Expected downtime vs. time interval T

The results show that the inspection interval that gives the minimum expected downtime for this problem is T= 25 hours. This means that inspection will take place every 25 hours and will have an expected downtime because of failure D(T)= 0.02038.

Using the same parameters stated at the problem definition we determine the expected total cost per unit *C(T).* Assume that the Cost of breakdown repair C_b = 5000, Cost of preventive maintenance C_{pm} = 2000, and the Inspection cost C_i =2500. The expected total cost per unit is obtained using the expected total cost equation obtained in the previous section. Applying the parameters into the equation:

$$C(T) = \frac{C_b kTP(T) + C_{pm} kT\big(1 - P(T)\big) + (1 - H_f)C_i}{T + (1 + H_f)d}$$

$$= \frac{5000 * 0.1 * TP(T) + 2000 * 0.1 * T\big(1 - P(T)\big) + (1 - 0.569)2500}{T + (1 + 0.569)0.35}$$

$$= \frac{500TP(T) + 200T\big(1 - P(T)\big) + 1077.5}{T + 0.5492}$$

The method of obtaining the time interval *T* that minimizes the expected total cost per unit time is through numerical analysis. The values of P(T) are used from previous table and the table below shows the values of *T* and their corresponding *C(T).*

T	C(T)	T	C(T)	T	C(T)
1	824.6605	34	298.4529	67	378.7712
2	579.7944	35	301.2585	68	380.5003
3	473.1286	36	304.0945	69	382.1892
4	413.6103	37	306.9508	70	383.8385
5	375.8199	38	309.8182	71	385.4484
6	349.8632	39	312.6887	72	387.0192
7	331.0883	40	315.5549	73	388.5512
8	317.0201	41	318.4103	74	390.0446
9	306.22	42	321.2487	75	391.4998
10	297.7951	43	324.0648	76	392.9172
11	291.1616	44	326.8536	77	394.2981
12	285.922	45	329.6106	78	395.6438
13	281.7958	46	332.3316	79	396.9556
14	278.58	47	335.0129	80	398.2349
15	276.1235	48	337.651	81	399.483
16	274.312	49	340.2426	82	400.7004
17	273.057	50	342.7849	83	401.8889
18	272.2893	51	345.2756	84	403.0493
19	271.9536	52	347.7155	85	404.1826
20	272.0057	53	350.1055	86	405.2897
21	272.4094	54	352.4465	87	406.3715
22	273.1348	55	354.7396	88	407.4289
23	274.1574	56	356.9855	89	408.4626
24	275.4565	57	359.1851	90	409.4735
25	277.0145	58	361.339	91	410.4624
26	278.8126	59	363.448	92	411.4298
27	280.8182	60	365.5127	93	412.3766
28	282.9993	61	367.5337	94	413.3034
29	285.3285	62	369.5115	95	414.2107
30	287.7817	63	371.4468	96	415.0992
31	290.338	64	373.34	97	415.9696
32	292.9791	65	375.1915	98	416.8223
33	295.6888	66	377.0017	99	417.6578

Figure 34: Expected total cost with respect to time interval T

After obtaining the expected downtime for each inspection period, the inspection period is plotted against the expected downtime. The next figure illustrates the results.

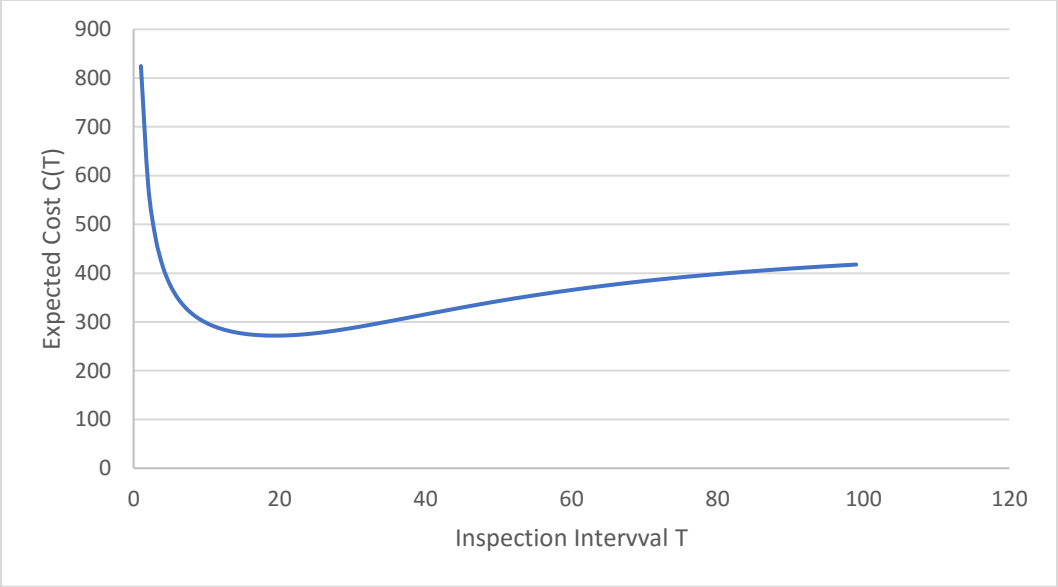

Figure 35: Expected total cost vs. time interval T

The results show that the inspection interval that gives the minimum expected cost with the assumed costs for this problem is T= 19 hours. This means that inspection will take place every 14 hours and will have an expected cost C(T) = 271.954.

CHAPTER 5

CONCLUSION

5.1 Summary

This thesis proposes first a research on the performance shaping factors that affect various maintenance activities. The common performance shaping factors that are collected are then classified into a two-hierarchy classification model. The first hierarchy divides the performance shaping factors into internal and external factors. The second hierarchy divides internal factors into person and knowledge and the external factors into environment and system factors that affect the maintenance activities.

The thesis then proposes two extensions to the delay time model to incorporate the human factors into the model. The first model incorporates the human factors by making the inspection time parameter based on three performance shaping factors. The three factors are the workers' experience level, fatigue level, and the seriousness level. The second model includes the incorporation of human factors in two parts the inspection time as in the first model and the

delay time. The delay time depends on four factors that are the characteristics of the item concerned, type of defect, nature of inspection, and the experience of the person inspecting. Both models were developed using fuzzy logic designer in MATLAB program. The objective of both models was to minimize the expected downtime and the expected total cost.

The first model showed that the inspection period compared to the original model is increased which decreases the expected total cost. The expected downtime was increased slightly. The second model included two fuzzy models to model the delay time, the probability density function of the model was obtained from the output of the fuzzy inference system.

5.2 Future Extensions

As a future development and extensions to the developed models, different objective functions could be targeted. One of these objectives could be to maximize the availability of the machine or object concerned. Researchers could also look into using different distributions when developing the membership functions. The distributions used in building the inputs and outputs in the fuzzy logic model are triangular distributions, these could be changed into more general distributions to study the effect of changing the distribution on the model.

The developed model applied to the delay time model could also be applied to other extensions of the delay time model such as the extension were imperfect inspections are modelled. Another extension that the developed model could be applied to is the multi-component system instead of the single component system.

One last possible extension that could be applied as further work is that the human factors could be incorporated and applied to more parameters of the delay time model, hence the whole model could be turned into a fuzzy model instead of a mathematical model.

Appendix A

Fuzzy Inference System of Human Factors

		IF							THEN	
Concerned Item		Criticality		Adequacy		Experience			Output	
Very Easy	0.20	No Criticality	0.20	Low	1.00	Low	1.00		Medium	0.60
Very Easy	0.20	No Criticality	0.20	Low	1.00	Medium	0.67		Low	0.52
Very Easy	0.20	No Criticality	0.20	Low	1.00	High	0.33		Low	0.43
Very Easy	0.20	No Criticality	0.20	Medium	0.67	Low	1.00		Low	0.52
Very Easy	0.20	No Criticality	0.20	Medium	0.67	Medium	0.67		Low	0.43
Very Easy	0.20	No Criticality	0.20	Medium	0.67	High	0.33		Very Low	0.35
Very Easy	0.20	No Criticality	0.20	High	0.33	Low	1.00		Low	0.43
Very Easy	0.20	No Criticality	0.20	High	0.33	Medium	0.67		Very Low	0.35
Very Easy	0.20	No Criticality	0.20	High	0.33	High	0.33		Very Low	0.27
Very Easy	0.20	Low Criticality	0.40	Low	1.00	Low	1.00		Medium	0.65
Very Easy	0.20	Low Criticality	0.40	Low	1.00	Medium	0.67		Medium	0.57
Very Easy	0.20	Low Criticality	0.40	Low	1.00	High	0.33		Low	0.48
Very Easy	0.20	Low Criticality	0.40	Medium	0.67	Low	1.00		Medium	0.57
Very Easy	0.20	Low Criticality	0.40	Medium	0.67	Medium	0.67		Low	0.48
Very Easy	0.20	Low Criticality	0.40	Medium	0.67	High	0.33		Low	0.40
Very Easy	0.20	Low Criticality	0.40	High	0.33	Low	1.00		Low	0.48
Very Easy	0.20	Low Criticality	0.40	High	0.33	Medium	0.67		Low	0.40
Very Easy	0.20	Low Criticality	0.40	High	0.33	High	0.33		Very Low	0.32
Very Easy	0.20	Regular Criticality	0.60	Low	1.00	Low	1.00		High	0.70
Very Easy	0.20	Regular Criticality	0.60	Low	1.00	Medium	0.67		Medium	0.62
Very Easy	0.20	Regular Criticality	0.60	Low	1.00	High	0.33		Medium	0.53
Very Easy	0.20	Regular Criticality	0.60	Medium	0.67	Low	1.00		Medium	0.62
Very Easy	0.20	Regular Criticality	0.60	Medium	0.67	Medium	0.67		Medium	0.53
Very Easy	0.20	Regular Criticality	0.60	Medium	0.67	High	0.33		Low	0.45
Very Easy	0.20	Regular Criticality	0.60	High	0.33	Low	1.00		Medium	0.53
Very Easy	0.20	Regular Criticality	0.60	High	0.33	Medium	0.67		Low	0.45

Very Easy	0.20	Regular Criticality	0.60	High	0.33	High	0.33		Low	0.37
Very Easy	0.20	Critical	0.80	Low	1.00	Low	1.00		High	0.75
Very Easy	0.20	Critical	0.80	Low	1.00	Medium	0.67		Medium	0.67
Very Easy	0.20	Critical	0.80	Low	1.00	High	0.33		Medium	0.58
Very Easy	0.20	Critical	0.80	Medium	0.67	Low	1.00		Medium	0.67
Very Easy	0.20	Critical	0.80	Medium	0.67	Medium	0.67		Medium	0.58
Very Easy	0.20	Critical	0.80	Medium	0.67	High	0.33		Low	0.50
Very Easy	0.20	Critical	0.80	High	0.33	Low	1.00		Medium	0.58
Very Easy	0.20	Critical	0.80	High	0.33	Medium	0.67		Low	0.50
Very Easy	0.20	Critical	0.80	High	0.33	High	0.33		Low	0.42
Very Easy	0.20	Highly Critical	1.00	Low	1.00	Low	1.00		High	0.80
Very Easy	0.20	Highly Critical	1.00	Low	1.00	Medium	0.67		High	0.72
Very Easy	0.20	Highly Critical	1.00	Low	1.00	High	0.33		Medium	0.63
Very Easy	0.20	Highly Critical	1.00	Medium	0.67	Low	1.00		High	0.72
Very Easy	0.20	Highly Critical	1.00	Medium	0.67	Medium	0.67		Medium	0.63
Very Easy	0.20	Highly Critical	1.00	Medium	0.67	High	0.33		Medium	0.55
Very Easy	0.20	Highly Critical	1.00	High	0.33	Low	1.00		Medium	0.63
Very Easy	0.20	Highly Critical	1.00	High	0.33	Medium	0.67		Medium	0.55
Very Easy	0.20	Highly Critical	1.00	High	0.33	High	0.33		Low	0.47
Easy	0.40	No Criticality	0.20	Low	1.00	Low	1.00		Medium	0.65
Easy	0.40	No Criticality	0.20	Low	1.00	Medium	0.67		Medium	0.57
Easy	0.40	No Criticality	0.20	Low	1.00	High	0.33		Low	0.48
Easy	0.40	No Criticality	0.20	Medium	0.67	Low	1.00		Medium	0.57
Easy	0.40	No Criticality	0.20	Medium	0.67	Medium	0.67		Low	0.48
Easy	0.40	No Criticality	0.20	Medium	0.67	High	0.33		Low	0.40
Easy	0.40	No Criticality	0.20	High	0.33	Low	1.00		Low	0.48
Easy	0.40	No Criticality	0.20	High	0.33	Medium	0.67		Low	0.40
Easy	0.40	No Criticality	0.20	High	0.33	High	0.33		Very Low	0.32
Easy	0.40	Low Criticality	0.40	Low	1.00	Low	1.00		High	0.70
Easy	0.40	Low Criticality	0.40	Low	1.00	Medium	0.67		Medium	0.62
Easy	0.40	Low Criticality	0.40	Low	1.00	High	0.33		Medium	0.53
Easy	0.40	Low Criticality	0.40	Medium	0.67	Low	1.00		Medium	0.62
Easy	0.40	Low Criticality	0.40	Medium	0.67	Medium	0.67		Medium	0.53
Easy	0.40	Low Criticality	0.40	Medium	0.67	High	0.33		Low	0.45
Easy	0.40	Low Criticality	0.40	High	0.33	Low	1.00		Medium	0.53
Easy	0.40	Low Criticality	0.40	High	0.33	Medium	0.67		Low	0.45
Easy	0.40	Low Criticality	0.40	High	0.33	High	0.33		Low	0.37
Easy	0.40	Regular Criticality	0.60	Low	1.00	Low	1.00		High	0.75
Easy	0.40	Regular Criticality	0.60	Low	1.00	Medium	0.67		Medium	0.67
Easy	0.40	Regular Criticality	0.60	Low	1.00	High	0.33		Medium	0.58

Easy	0.40	Regular Criticality	0.60	Medium	0.67	Low	1.00		Medium	0.67
Easy	0.40	Regular Criticality	0.60	Medium	0.67	Medium	0.67		Medium	0.58
Easy	0.40	Regular Criticality	0.60	Medium	0.67	High	0.33		Low	0.50
Easy	0.40	Regular Criticality	0.60	High	0.33	Low	1.00		Medium	0.58
Easy	0.40	Regular Criticality	0.60	High	0.33	Medium	0.67		Low	0.50
Easy	0.40	Regular Criticality	0.60	High	0.33	High	0.33		Low	0.42
Easy	0.40	Critical	0.80	Low	1.00	Low	1.00		High	0.80
Easy	0.40	Critical	0.80	Low	1.00	Medium	0.67		High	0.72
Easy	0.40	Critical	0.80	Low	1.00	High	0.33		Medium	0.63
Easy	0.40	Critical	0.80	Medium	0.67	Low	1.00		High	0.72
Easy	0.40	Critical	0.80	Medium	0.67	Medium	0.67		Medium	0.63
Easy	0.40	Critical	0.80	Medium	0.67	High	0.33		Medium	0.55
Easy	0.40	Critical	0.80	High	0.33	Low	1.00		Medium	0.63
Easy	0.40	Critical	0.80	High	0.33	Medium	0.67		Medium	0.55
Easy	0.40	Critical	0.80	High	0.33	High	0.33		Low	0.47
Easy	0.40	Highly Critical	1.00	Low	1.00	Low	1.00		Very High	0.85
Easy	0.40	Highly Critical	1.00	Low	1.00	Medium	0.67		High	0.77
Easy	0.40	Highly Critical	1.00	Low	1.00	High	0.33		High	0.68
Easy	0.40	Highly Critical	1.00	Medium	0.67	Low	1.00		High	0.77
Easy	0.40	Highly Critical	1.00	Medium	0.67	Medium	0.67		High	0.68
Easy	0.40	Highly Critical	1.00	Medium	0.67	High	0.33		Medium	0.60
Easy	0.40	Highly Critical	1.00	High	0.33	Low	1.00		High	0.68
Easy	0.40	Highly Critical	1.00	High	0.33	Medium	0.67		Medium	0.60
Easy	0.40	Highly Critical	1.00	High	0.33	High	0.33		Low	0.52
Normal	0.60	No Criticality	0.20	Low	1.00	Low	1.00		High	0.70
Normal	0.60	No Criticality	0.20	Low	1.00	Medium	0.67		Medium	0.62
Normal	0.60	No Criticality	0.20	Low	1.00	High	0.33		Medium	0.53
Normal	0.60	No Criticality	0.20	Medium	0.67	Low	1.00		Medium	0.62
Normal	0.60	No Criticality	0.20	Medium	0.67	Medium	0.67		Medium	0.53
Normal	0.60	No Criticality	0.20	Medium	0.67	High	0.33		Low	0.45
Normal	0.60	No Criticality	0.20	High	0.33	Low	1.00		Medium	0.53
Normal	0.60	No Criticality	0.20	High	0.33	Medium	0.67		Low	0.45
Normal	0.60	No Criticality	0.20	High	0.33	High	0.33		Low	0.37
Normal	0.60	Low Criticality	0.40	Low	1.00	Low	1.00		High	0.75
Normal	0.60	Low Criticality	0.40	Low	1.00	Medium	0.67		Medium	0.67
Normal	0.60	Low Criticality	0.40	Low	1.00	High	0.33		Medium	0.58
Normal	0.60	Low Criticality	0.40	Medium	0.67	Low	1.00		Medium	0.67
Normal	0.60	Low Criticality	0.40	Medium	0.67	Medium	0.67		Medium	0.58
Normal	0.60	Low Criticality	0.40	Medium	0.67	High	0.33		Low	0.50

Normal	0.60	Low Criticality	0.40	High	0.33	Low	1.00		Medium	0.58
Normal	0.60	Low Criticality	0.40	High	0.33	Medium	0.67		Low	0.50
Normal	0.60	Low Criticality	0.40	High	0.33	High	0.33		Low	0.42
Normal	0.60	Regular Criticality	0.60	Low	1.00	Low	1.00		High	0.80
Normal	0.60	Regular Criticality	0.60	Low	1.00	Medium	0.67		High	0.72
Normal	0.60	Regular Criticality	0.60	Low	1.00	High	0.33		Medium	0.63
Normal	0.60	Regular Criticality	0.60	Medium	0.67	Low	1.00		High	0.72
Normal	0.60	Regular Criticality	0.60	Medium	0.67	Medium	0.67		Medium	0.63
Normal	0.60	Regular Criticality	0.60	Medium	0.67	High	0.33		Medium	0.55
Normal	0.60	Regular Criticality	0.60	High	0.33	Low	1.00		Medium	0.63
Normal	0.60	Regular Criticality	0.60	High	0.33	Medium	0.67		Medium	0.55
Normal	0.60	Regular Criticality	0.60	High	0.33	High	0.33		Low	0.47
Normal	0.60	Critical	0.80	Low	1.00	Low	1.00		Very High	0.85
Normal	0.60	Critical	0.80	Low	1.00	Medium	0.67		High	0.77
Normal	0.60	Critical	0.80	Low	1.00	High	0.33		High	0.68
Normal	0.60	Critical	0.80	Medium	0.67	Low	1.00		High	0.77
Normal	0.60	Critical	0.80	Medium	0.67	Medium	0.67		High	0.68
Normal	0.60	Critical	0.80	Medium	0.67	High	0.33		Medium	0.60
Normal	0.60	Critical	0.80	High	0.33	Low	1.00		High	0.68
Normal	0.60	Critical	0.80	High	0.33	Medium	0.67		Medium	0.60
Normal	0.60	Critical	0.80	High	0.33	High	0.33		Low	0.52
Normal	0.60	Highly Critical	1.00	Low	1.00	Low	1.00		Very High	0.90
Normal	0.60	Highly Critical	1.00	Low	1.00	Medium	0.67		High	0.82
Normal	0.60	Highly Critical	1.00	Low	1.00	High	0.33		High	0.73
Normal	0.60	Highly Critical	1.00	Medium	0.67	Low	1.00		High	0.82
Normal	0.60	Highly Critical	1.00	Medium	0.67	Medium	0.67		High	0.73
Normal	0.60	Highly Critical	1.00	Medium	0.67	High	0.33		Medium	0.65
Normal	0.60	Highly Critical	1.00	High	0.33	Low	1.00		High	0.73
Normal	0.60	Highly Critical	1.00	High	0.33	Medium	0.67		Medium	0.65
Normal	0.60	Highly Critical	1.00	High	0.33	High	0.33		Medium	0.57
Hard	0.80	No Criticality	0.20	Low	1.00	Low	1.00		High	0.75
Hard	0.80	No Criticality	0.20	Low	1.00	Medium	0.67		Medium	0.67
Hard	0.80	No Criticality	0.20	Low	1.00	High	0.33		Medium	0.58
Hard	0.80	No Criticality	0.20	Medium	0.67	Low	1.00		Medium	0.67
Hard	0.80	No Criticality	0.20	Medium	0.67	Medium	0.67		Medium	0.58
Hard	0.80	No Criticality	0.20	Medium	0.67	High	0.33		Low	0.50
Hard	0.80	No Criticality	0.20	High	0.33	Low	1.00		Medium	0.58

Hard	0.80	No Criticality	0.20	High	0.33	Medium	0.67		Low	0.50
Hard	0.80	No Criticality	0.20	High	0.33	High	0.33		Low	0.42
Hard	0.80	Low Criticality	0.40	Low	1.00	Low	1.00		High	0.80
Hard	0.80	Low Criticality	0.40	Low	1.00	Medium	0.67		High	0.72
Hard	0.80	Low Criticality	0.40	Low	1.00	High	0.33		Medium	0.63
Hard	0.80	Low Criticality	0.40	Medium	0.67	Low	1.00		High	0.72
Hard	0.80	Low Criticality	0.40	Medium	0.67	Medium	0.67		Medium	0.63
Hard	0.80	Low Criticality	0.40	Medium	0.67	High	0.33		Medium	0.55
Hard	0.80	Low Criticality	0.40	High	0.33	Low	1.00		Medium	0.63
Hard	0.80	Low Criticality	0.40	High	0.33	Medium	0.67		Medium	0.55
Hard	0.80	Low Criticality	0.40	High	0.33	High	0.33		Low	0.47
Hard	0.80	Regular Criticality	0.60	Low	1.00	Low	1.00		Very High	0.85
Hard	0.80	Regular Criticality	0.60	Low	1.00	Medium	0.67		High	0.77
Hard	0.80	Regular Criticality	0.60	Low	1.00	High	0.33		High	0.68
Hard	0.80	Regular Criticality	0.60	Medium	0.67	Low	1.00		High	0.77
Hard	0.80	Regular Criticality	0.60	Medium	0.67	Medium	0.67		High	0.68
Hard	0.80	Regular Criticality	0.60	Medium	0.67	High	0.33		Medium	0.60
Hard	0.80	Regular Criticality	0.60	High	0.33	Low	1.00		High	0.68
Hard	0.80	Regular Criticality	0.60	High	0.33	Medium	0.67		Medium	0.60
Hard	0.80	Regular Criticality	0.60	High	0.33	High	0.33		Low	0.52
Hard	0.80	Critical	0.80	Low	1.00	Low	1.00		Very High	0.90
Hard	0.80	Critical	0.80	Low	1.00	Medium	0.67		High	0.82
Hard	0.80	Critical	0.80	Low	1.00	High	0.33		High	0.73
Hard	0.80	Critical	0.80	Medium	0.67	Low	1.00		High	0.82
Hard	0.80	Critical	0.80	Medium	0.67	Medium	0.67		High	0.73
Hard	0.80	Critical	0.80	Medium	0.67	High	0.33		Medium	0.65
Hard	0.80	Critical	0.80	High	0.33	Low	1.00		High	0.73
Hard	0.80	Critical	0.80	High	0.33	Medium	0.67		Medium	0.65
Hard	0.80	Critical	0.80	High	0.33	High	0.33		Medium	0.57
Hard	0.80	Highly Critical	1.00	Low	1.00	Low	1.00		Very High	0.95
Hard	0.80	Highly Critical	1.00	Low	1.00	Medium	0.67		Very High	0.87
Hard	0.80	Highly Critical	1.00	Low	1.00	High	0.33		High	0.78
Hard	0.80	Highly Critical	1.00	Medium	0.67	Low	1.00		Very High	0.87
Hard	0.80	Highly Critical	1.00	Medium	0.67	Medium	0.67		High	0.78
Hard	0.80	Highly Critical	1.00	Medium	0.67	High	0.33		High	0.70
Hard	0.80	Highly Critical	1.00	High	0.33	Low	1.00		High	0.78
Hard	0.80	Highly Critical	1.00	High	0.33	Medium	0.67		High	0.70

Hard	0.80	Highly Critical	1.00	High	0.33	High	0.33		Medium	0.62
Very Hard	1.00	No Criticality	0.20	Low	1.00	Low	1.00		High	0.80
Very Hard	1.00	No Criticality	0.20	Low	1.00	Medium	0.67		High	0.72
Very Hard	1.00	No Criticality	0.20	Low	1.00	High	0.33		Medium	0.63
Very Hard	1.00	No Criticality	0.20	Medium	0.67	Low	1.00		High	0.72
Very Hard	1.00	No Criticality	0.20	Medium	0.67	Medium	0.67		Medium	0.63
Very Hard	1.00	No Criticality	0.20	Medium	0.67	High	0.33		Medium	0.55
Very Hard	1.00	No Criticality	0.20	High	0.33	Low	1.00		Medium	0.63
Very Hard	1.00	No Criticality	0.20	High	0.33	Medium	0.67		Medium	0.55
Very Hard	1.00	No Criticality	0.20	High	0.33	High	0.33		Low	0.47
Very Hard	1.00	Low Criticality	0.40	Low	1.00	Low	1.00		Very High	0.85
Very Hard	1.00	Low Criticality	0.40	Low	1.00	Medium	0.67		High	0.77
Very Hard	1.00	Low Criticality	0.40	Low	1.00	High	0.33		High	0.68
Very Hard	1.00	Low Criticality	0.40	Medium	0.67	Low	1.00		High	0.77
Very Hard	1.00	Low Criticality	0.40	Medium	0.67	Medium	0.67		High	0.68
Very Hard	1.00	Low Criticality	0.40	Medium	0.67	High	0.33		Medium	0.60
Very Hard	1.00	Low Criticality	0.40	High	0.33	Low	1.00		High	0.68
Very Hard	1.00	Low Criticality	0.40	High	0.33	Medium	0.67		Medium	0.60
Very Hard	1.00	Low Criticality	0.40	High	0.33	High	0.33		Low	0.52
Very Hard	1.00	Regular Criticality	0.60	Low	1.00	Low	1.00		Very High	0.90
Very Hard	1.00	Regular Criticality	0.60	Low	1.00	Medium	0.67		High	0.82
Very Hard	1.00	Regular Criticality	0.60	Low	1.00	High	0.33		High	0.73
Very Hard	1.00	Regular Criticality	0.60	Medium	0.67	Low	1.00		High	0.82
Very Hard	1.00	Regular Criticality	0.60	Medium	0.67	Medium	0.67		High	0.73
Very Hard	1.00	Regular Criticality	0.60	Medium	0.67	High	0.33		Medium	0.65
Very Hard	1.00	Regular Criticality	0.60	High	0.33	Low	1.00		High	0.73
Very Hard	1.00	Regular Criticality	0.60	High	0.33	Medium	0.67		Medium	0.65
Very Hard	1.00	Regular Criticality	0.60	High	0.33	High	0.33		Medium	0.57
Very Hard	1.00	Critical	0.80	Low	1.00	Low	1.00		Very High	0.95
Very Hard	1.00	Critical	0.80	Low	1.00	Medium	0.67		Very High	0.87
Very Hard	1.00	Critical	0.80	Low	1.00	High	0.33		High	0.78
Very Hard	1.00	Critical	0.80	Medium	0.67	Low	1.00		Very High	0.87
Very Hard	1.00	Critical	0.80	Medium	0.67	Medium	0.67		High	0.78
Very Hard	1.00	Critical	0.80	Medium	0.67	High	0.33		High	0.70
Very Hard	1.00	Critical	0.80	High	0.33	Low	1.00		High	0.78
Very Hard	1.00	Critical	0.80	High	0.33	Medium	0.67		High	0.70
Very Hard	1.00	Critical	0.80	High	0.33	High	0.33		Medium	0.62

Very Hard	1.00	Highly Critical	1.00	Low	1.00	Low	1.00		Very High	1.00
Very Hard	1.00	Highly Critical	1.00	Low	1.00	Medium	0.67		Very High	0.92
Very Hard	1.00	Highly Critical	1.00	Low	1.00	High	0.33		High	0.83
Very Hard	1.00	Highly Critical	1.00	Medium	0.67	Low	1.00		Very High	0.92
Very Hard	1.00	Highly Critical	1.00	Medium	0.67	Medium	0.67		High	0.83
Very Hard	1.00	Highly Critical	1.00	Medium	0.67	High	0.33		High	0.75
Very Hard	1.00	Highly Critical	1.00	High	0.33	Low	1.00		High	0.83
Very Hard	1.00	Highly Critical	1.00	High	0.33	Medium	0.67		High	0.75
Very Hard	1.00	Highly Critical	1.00	High	0.33	High	0.33		Medium	0.67

REFERENCES

Abdel-Hameed M., (1995), Inspection, maintenance and replacement models, Computers and Operations Research, V22, 4, 435 – 441.

Akbarov, A., Christer, A. H., & Wang, W. (2008). Problem identification in maintenance modelling: a case study. International journal of production research, 46(4), 1031-1046.

Al-Najjar, B., Alsyouf, I., 2003. Selecting the most efficient maintenance approach using fuzzy multiple criteria decision making. International Journal of Production Economics 84 (1), 85–100.

AMCP 706-134, *Maintainability Guide for Design*, U.S. Army Material Command, Department of the Army, Washington, D.C., 1972.

Baker, K. R., & Trietsch, D. (2009). Principles of sequencing and scheduling. Hoboken, NJ: Wiley.

Baker, R. D., & Wang, W. (1991). Estimating the delay-time distribution of faults in repairable machinery from failure data. IMA Journal of Management Mathematics, 3(4), 259-281.

Baker, R. D., & Wang, W. (1993). Developing and testing the delay-time model. Journal of the Operational Research Society, 44(4), 361-374.

Baraldi P, Balestrero A, Compare M, Benetrix L, Despujols A, Zio E., 2012. A modeling framework for maintenance optimization of electrical components based on fuzzy logic and effective age. Quality Reliability Engineering International 2013; 29:385–405.

Berrade, M. D., Scarf, P. A., & Cavalcante, C. A. V. (2017). A study of postponed replacement in a delay time model. Reliability Engineering & System Safety, 168, 70-79.

Boring, L.R., (2010). How Many Performance Shaping Factors are Necessary for Human Reliability Analysis? Idaho National Laboratory. Retrieved March 27, 2018.

Carr, M. J., & Christer, A. H. (2003). Incorporating the potential for human error in maintenance models. Journal of the Operational Research Society, 54(12), 1249-1253. doi: 10.1057/palgrave.jors.2601634.

Cassady, C. R., & Kutanoglu, E. (2003). Minimizing Job Tardiness Using Integrated Preventive Maintenance Planning and Production Scheduling. IIE Transactions, 35(6), 503-513. doi:10.1080/07408170304416.

Cassady, C., & Kutanoglu, E. (2005). Integrating Preventive Maintenance Planning and Production Scheduling for a Single Machine. IEEE Transactions on Reliability, 54(2), 304-309. doi:10.1109/tr.2005.845967

Chen, X., Xiao, L., Zhang, X., Xiao, W., & Li, J. (2015). An integrated model of production scheduling and maintenance planning under imperfect preventive maintenance. Eksploatacja i Niezawodnosc - Maintenance and Reliability, 17(1), 70-79. doi:10.17531/ein.2015.1.10.

Christer, A H and Waller, W M, (1984), Delay time Models of Industrial Inspection Maintenance Problems, J. Opl. Res. Soc., 35, 401-406, 1984.

Christer, A. H., & Wang, W. (1995). A delay-time-based maintenance model of a multi-component system. IMA Journal of Management Mathematics, 6(2), 205-222.

Christer, A. H., Wang, W., Choi, K., & Sharp, J. (1998). The delay-time modelling of preventive maintenance of plant given limited PM data and selective repair at PM. IMA Journal of Management Mathematics, 9(4), 355-379.

Christensen, J.M. and Howard, J.M. 1981, Field experience in maintenance, in *Human Detection and Diagnosis of System Failures*, J. Rasmussen and W.B. Rouse, eds., Plenum Press, New York, 111–133.

Circular 243-AN/151, 1995, Human Factors in Aircraft Maintenance and Inspection, International Civil Aviation Organization, Montreal, Canada.

Coudert, T., Grabot, B., Archimede, B., 2002. Production/maintenance cooperative scheduling using multi-agents and fuzzy logic. International Journal of Production Research 40 (18), 4611–4632.

Daniels, R.W. 1985, The Formula for Improve Plant Maintainability, Must Include Human Factors, *Proceedings of the IEEE Conference on Human Factors and Nuclear Safety*, pp.242-244.

Dhillon, B.S. 1990, Human Error Data Banks, *Microelectrics and Reliability*, Vol. 30, pp. 963-971.

Dhillon, B.S. 1986, *Human Reliability: With Human Factors*, Pergamon Press, New York.

Dhillon, B., & Liu, Y. 2006. Human error in maintenance: a review. Journal of Quality in Maintenance Engineering, 12(1), 21-36. doi:10.1108/13552510610654510.

Driessen, J. P. C., Peng, H., & van Houtum, G. J. (2017). Maintenance optimization under non-constant probabilities of imperfect inspections. Reliability Engineering & System Safety, 165, 115-123.

Hadidi, L. A., Turki, U. M., & Rahim, A. (2012). Integrated models in production planning and scheduling, maintenance and quality: a review. International Journal of Industrial and Systems Engineering, 10(1), 21. doi:10.1504/ijise.2012.044042.

Hadidi, L. A., Turki, U. M., & Rahim, M. A. (2011). An integrated cost model for production scheduling and perfect maintenance. International Journal of Mathematics in Operational Research, 3(4), 395. doi:10.1504/ijmor.2011.040875.

Hadidi, L. A., Turki, U. M., & Rahim, M. A. (2012). Joint job scheduling and preventive maintenance on a single machine. International Journal of Operational Research, 13(2), 174. doi:10.1504/ijor.2012.045185.

Hasegawa, T., Kemeda, A. 1998, Analysis and Evaluation of Human Error Events in Nuclear Power Plants, Presented at the Meeting of IAEA's CRP on "Collection and Classification of Human Reliability Data for Use in Probabilistic Safety Assessments,". Available from the Institute of Human Factors, Nuclear Power Engineering Corporation,3-17-1, Toranomon, Minatu-Ku, Tokyo, Japan.

Hennequin, S., Arango, G., & Rezg, N. (2009). Optimization of imperfect maintenance based on fuzzy logic for a single-stage single-product production system. Journal of Quality in Maintenance Engineering, 15(4), 412-429. doi:10.1108/13552510910997779.

Human Factors in Airline Maintenance 1997: A Study of Incident Reports, Bureau of Air Safety Inspection, Department of Transport and Regional Development, Canberra, Australia.

Jeffries, M., Lai, E., Plantenberg, D., Hull, B., 2001. A fuzzy approach to the condition monitoring of a packaging plant. Journal of Materials Processing Technology 109 (1–2), 83–89.

Latino, C.J. 1999, Hidden Treasure: Eliminating Chronic Failures Can Cut Maintenance Costs up to 60%, Report, Reliability Center, Hopewell, Virginia.

Lau, H. C.W., Pang, W. K., and Wong, C.W.Y. 2002. Methodology for monitoring supply chain performance: a fuzzy logic approach. Logistic Inf. Management, 15(4), 271–280.

Li, S. 2000 The development of a hybrid intelligent system for developing marketing strategies. Decision Support System, 7(4), 395–409.

Lopes, R. S., Cavalcante, C. A., & Alencar, M. H. (2015). Delay-time inspection model with dimensioning maintenance teams: A study of a company leasing construction equipment. Computers & Industrial Engineering, 88, 341-349.

Lu, K., Sy, C., 2009. A real-time decision-making of maintenance using fuzzy agent. Expert Systems with Application 36 (2), 2691–2698.

Marx, D.A. 1998, *Learning from Our Mistakes: A Review of Maintenance Error Investigation and Analysis Systems (with Recommendations to the FAA*), Federal Aviation Administration (FAA), Washington, D.C.

Meister, D. 1976, *Human Factors: Theory and Practice*, John Wiley & Sons, New York.

Meister, D. 1984, Human Reliability, in *Human Factors Review*, edited by F.A., Muckler, Human Factors Society, Santa Monica, CA, pp. 13-53.

Meister, D. 1962, The problem of human-initiated failures, in *Proceedings of the 8th National Symposium on Reliability and Quality Control*, 234–239.

Nodem, F., Kenne, J., Gharbi, A., 2009. Hierarchical decision making in production and repair/replacement planning with imperfect repairs under uncertainties. European Journal of Operational Research 198 (1), 173–189.

Okoh, P., Haugen, S., 2014. A study of maintenance-related major accident cases in the 21st century. Process Saf. Environ. Protect. 92, 346–356. https://doi.org/10.1016/j.psep.2014.03.001.

Petrovic-Lazarevic, S. and Wong, A 2000. Fuzzy control model in the hospitality industry. International Journal Agile Management Systems., 2(2), 156–162

Pillay, A., Wang, J., Wall, A. D., & Ruxton, T. (2001). A maintenance study of fishing vessel equipment using delay-time analysis. Journal of Quality in Maintenance Engineering, 7(2), 118-128.

Poppe, J., Basten, R. J., Boute, R. N., & Lambrecht, M. R. (2017). Numerical study of inventory management under various maintenance policies. Reliability Engineering & System Safety,168, 262-273. doi: 10.1016/j.ress.2017.06.012

Pyy, P. 2001, An Analysis of Maintenance Failures at a Nuclear Power Plant, *Reliability Engineering and Systems Safety*, Vol.72, , pp.293-302.

Pyy, P. 1997, Laakso, K., Reiman, L., A Study of Human Errors Related to NPP Maintenance Activities, Proceedings pf the IEEE 6th Annual Human Factors Meeting, pp.12.23-12.28.

Reason, J. 1997, Human Factors in Nuclear Power Generation: A System's Perspective, *Nuclear Europe Worldscan*, Vol. 17, No. 5-6, pp.35-36.

Rigby, L.V. 1967, The Sandia human error rate bank (SHERB), Report No. SC-R-67-1150, Sandia Labs, Albuquerque, New Mexico.

R.K. Mobley 1990, An Introduction to Predictive Maintenance, Van Nostrand Reinhold, New York; Measuring maintenance performance-in search for a maintenance productivity index; TPM—Total productive maintenance: impact on competitiveness and a framework for successful implementation

Robinson, J.E., Deutsch, W.E., Rogers, J.G. 1970, The Field Maintenance Interface between Human Engineering and Maintainability Engineering, *Human Factors*, Vol. 12, pp. 253-259.

Sarfraz M. S. 2017, "Implementing a Preventive Maintenance Planning Model for Computer Numerical Control (CNC) Milling Machine", American Journal of Embedded Systems and Applications; 5(6): 44-47

Sheikhalishahi, M., Pintelon, L., & Azadeh, A. (2016). Human factors in maintenance: a review. Journal of Quality in Maintenance Engineering, 22(3), 218-237. doi:10.1108/jqme-12-2015-0064.

Sudiarso, A., Labib, A., 2002. A fuzzy logic approach to an integrated maintenance/ production scheduling algorithm. International Journal of Production Research 40 (13), 3121–3138.

Ung, S., Williams, V., Bonsall, S., and Wang, J. 2009 The risk assessment and management of port security using fuzzy modelling Mar. Technol., 46(2), 61–73.

Van Oosterom, C. D., Elwany, A. H., Çelebi, D., & Van Houtum, G. J. (2014). Optimal policies for a delay time model with postponed replacement. European Journal of Operational Research, 232(1), 186-197**.**

Verma AK, Srividya A, 2011. Ramesh PG. FIS based selection of CM system design parameters from a multi-objective optimization model using GA. International Journal System Assurance Engineering Management 2011; 2:14–20

Wang, W., Banjevic, D., & Pecht, M. (2010). A multi-component and multi-failure mode inspection model based on the delay time concept. Reliability Engineering & System Safety, 95(8), 912-920.

Wang, W., & Christer, A. H. (1997). A modelling procedure to optimize component safety inspection over a finite time horizon. Quality and reliability engineering international, 13(4), 217-224.

Wang, W., & Christer, A. H. (2003). Solution algorithms for a nonhomogeneous multi-component inspection model. Computers & Operations Research, 30(1), 19-34.

Wang, W. (2011). A joint spare part and maintenance inspection optimization model using the delay-time concept. Reliability Engineering & System Safety, 96(11), 1535-1541.

Wang, W. (2012). An overview of the recent advances in delay-time-based maintenance modelling. Reliability Engineering & System Safety, 106, 165-178.

Wen-Yuan, L. V., & Wang, W. (2006, October). Modelling preventive maintenance of production plant given estimated PM data and actual failure times. In Management Science and Engineering, 2006. ICMSE'06. 2006 International Conference on (pp. 387-390). IEEE.

Wilson, H. and McDonald, M. 1994, Critical problems in marketing planning: the potential of decision support system. J. Strategic Marketing, , 2, 249–269.

Yuniarto, M.N., Labib, A.W., 2006. Fuzzy adaptive preventive maintenance in a manufacturing control system: a step towards self-maintenance. International Journal of Production Research 44 (1), 159–180.

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