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ADETOYE AYOKUNLE ARIBISALA

CONTRIBUTIONS OF MAINTENANCE POLICIES FOR CENTRIFUGAL PUMPS USED IN AN IRON ORE CONCENTRATE PLANT

Recife

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Thesis presented to the Graduate Program in Production Engineering at the Federal University of Pernambuco, as a partial requirement for obtaining the title of Doctor of Philosophy (PhD) in Production Engineering.

Research area: Engineering Management

Supervisor: Prof. Dr. Cristiano Alexandre Virgínio Cavalcante.

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Dedicated to my dad, Prince Gbadebo Aribisala (in loving memory)

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ABSTRACT

Implementing an effective maintenance policy on industrial equipment is crucial to ensuring optimal performance. In particular, maintaining the optimal condition of centrifugal pumps, which play a critical role in various industrial processes such as the transportation of slurries and fluids, is of utmost importance. Hence, this thesis presents two studies related to the maintenance of centrifugal pumps used in the production of iron ore concentrates. The first study proposes a reinforcement learning approach for condition-based maintenance of the pumps, utilizing a variance gamma process degradation model to simulate the degradation process and recommend actions to minimize long-term maintenance costs. The study filled the gap in the literature by considering three performance features, namely pressure, temperature, and vibration, in modelling the state environment. The second study develops an integrated opportunistic maintenance policy for a cold-standby system consisting of a principal set of pumps and a standby set that is activated in the event of failure, utilizing the delay-time concept and defining two maintenance policies for combined optimization. The study's major contribution to knowledge is in the integrated policy that considers actions for the principal system and for the standby system as well. A sensitivity analysis was performed on the two models. The results obtained justified the robustness of the policies, and demonstrated potential for improving maintenance strategies in the iron ore industry and other industries utilizing similar equipment. The two works therefore provide valuable insights into improving maintenance policies for centrifugal pumps and highlight the importance of developing maintenance strategies at reduced costs.

Keywords: maintenance; reinforcement learning; delay-time; standby system; opportunistic maintenance; deterioration process

RESUMO

Implementar uma política de manutenção efetiva em equipamentos industriais é crucial para garantir o desempenho ideal. Em particular, manter a condição ótima de bombas centrífugas, que desempenham um papel crítico em vários processos industriais, como o transporte de lamas e fluidos, é de extrema importância. Por isso, esta tese apresenta dois estudos relacionados à manutenção de bombas centrífugas usadas na produção de concentrados de minério de ferro. O primeiro estudo propõe uma abordagem de aprendizado por reforço para manutenção baseada em condições das bombas, utilizando um modelo de degradação de processo gama variante para simular o processo de degradação e recomendar ações para minimizar os custos de manutenção a longo prazo. O estudo preencheu a lacuna na literatura ao considerar três características de desempenho, a saber, pressão, temperatura e vibração, na modelagem do ambiente de estado. O segundo estudo desenvolve uma política de manutenção oportunista integrada para um sistema de reserva frio composto por um conjunto principal de bombas e um conjunto reserva que é ativado em caso de falha, utilizando o conceito de delay-time e definindo duas políticas de manutenção para otimização combinada. A principal contribuição do estudo para o conhecimento está na política integrada que considera ações tanto para o sistema principal quanto para o sistema reserva. Uma análise de sensibilidade foi realizada nos dois modelos. Os resultados obtidos justificaram a robustez das políticas e demonstraram o potencial de melhoria das estratégias de manutenção na indústria de minério de ferro e outras indústrias que utilizam equipamentos semelhantes. Os dois trabalhos fornecem, portanto, insights valiosos para a melhoria das políticas de manutenção para bombas centrífugas e destacam a importância do desenvolvimento de estratégias de manutenção com custos reduzidos.

Palavras-chave: manutenção; aprendizado por reforço; tempo de atraso; sistema de espera; manutenção oportunista; processo de deterioração.

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1 INTRODUCTION

Centrifugal pumps have a wide range of applications in the water distribution networks, mining, chemical and industrial plants (CHEN et al., 2022; MARTINUS et al., 2022). As part of their function in industrial plants, they play a very prominent role in the beneficiation of iron ore concentrates at the National Iron Ore Mining Company, (NIOMCO) Itakpe, located in Nigeria. They constitute about 20% of the cost of all equipment purchases in an industrial plant, they also consume about 80% electricity and account for approximately 40% of maintenance expenditure (HASHIM, HASSAN, HAMID, 2020). The importance of centrifugal pumps in an iron ore processing plant cannot be overemphasized. Their major function involves the transportation of slurries from one point of the production process to the other (TOIT, CROZIER, 2012). These pumps are very important that when there is a blockage in any part of the production line, the whole production line is affected and the entire line stops running.

The production process line comprises of several pumps that need to be constantly monitored and maintained in order to reduce downtime and cost. The management of the company being studied expect the pumps to deliver at minimum cost. This means that production utilities must satisfy quantitative reliability requirements, while at the same time try to minimize their costs. The predominant expenditure for a utility is the cost of maintaining system assets, an example is through adopting maintenance measures (ALLAN et al., 1988). Research findings have shown that maintenance impacts on the reliability performance of a component, this will eventually reflect on the entire system since concentrate production process systems are made up of interconnected components (VRIGNAT, KRATZ, AVILA, 2022).

The major equipment failure in the production of iron ore concentrate which can stop production process is the pump. McKee et al. (2011) outlines the major failure modes inherent in a centrifugal pump. These includes among others; hydraulic failures, pressure pulsation, radial and axial thrust, suction/discharge recirculation, mechanical failures, lubrication failure and excessive vibrations. All the aforementioned faults result in decreased pump efficiency that progressively reduce the working life of the equipment. Therefore, there is an utmost need to develop effective optimal maintenance policies to mitigate against this.

Considering the aforementioned discussion, this thesis seeks to analyze some contributions towards deploying effective maintenance policy for centrifugal pumps in an iron ore concentrate production industry. The contributions analyzed involves studying how maintenance policies such as, condition-based maintenance based on the reinforcement learning algorithm, opportunistic maintenance based on the delay-time and inspection policies have on the centrifugal pump. In order to achieve this goal, the following problems and approach are solved in this thesis.

The first approach is a thorough literature review captured in chapter 2 that details the key concepts in this research. This includes such topics as; the delay-time, opportunistic maintenance, standby system, preparedness systems. Also, the reinforcement learning coupled with the algorithms used in the field are extensively discussed. The degradation processes deployed in modelling pump failure is also discussed.

Two major models are developed in this thesis so as to showcase the contributions of maintenance policies for centrifugal pump. The first work's major contribution is building a reinforcement learning model for optimal CBM policy on the centrifugal pump. The idea is based on the premise that in developing a robust RL algorithm, it will assist in learning the best action to take on the pump at every time-step or interaction as the pump degrades. This will invariably increase the availability of the centrifugal pumps. The developed RL will also help in solving the problem that is noticed in the industry where auxiliary pumps are switched on when the main pumps fail. The disadvantage of this is that the failed pump's life could be extended and repairs less costly if they were discovered prior to failure (MARTINUS et al., 2019). The impact of the degradation process on the pump was simulated by a variance gamma process on three health indicators (temperature, vibration and pressure) of the pump as against most works that considered only one health indicator (MITRA, MARWA, ESTELLE, 2022; SALEM, FOULADIRAD, DELOUX, 2021). Results showed that the agent was able to predict the optimal decision at each time step that will increase the availability of the equipment.

The second work involves developing an integrated maintenance policy for a set of principal and cold standby system in a set of centrifugal pumps using the delay-time concept. The system consists of two sets of centrifugal pumps. It is a series of parallel system configuration. The principal system set are in series, each pump in the principal set is connected in parallel to its corresponding standby pump. If a pump in the principal system fails, its corresponding back up pump takes over its functionality. This study aims to contribute to the development of an opportunistic inspection policy for backup systems by considering actions taken in the principal system that are not taken into account by the standby system. This approach provides a more comprehensive maintenance strategy that ensures that the backup pumps are always available for swap. The novelty of the work is in considering the relationship between the primary and backup systems using the delay time concept in modelling the system's degradation. The timing of actions such as replacement, inspection, and failure are also considered. Another contribution to knowledge arises from the work of Sinisterra et al. (2023). The work has its central hypothesis on the failure process in two stages. This process was modeled on the concept of delay time. This same concept was fundamental for the development of the integrated inspection model, presented in chapter 4. In an evolutionary way, the model presented in chapter 4 promotes a scenario with less production interruptions than the model proposed in the article in Sinisterra et al. (2023), since there is a pump backup linked to each main pump. This aspect gave rise to a deeper investigation into the redundancy of critical items in job sequencing problems, which is already in full development. In this sense, a synergistic effect is observed in which the student's participation brought new perspectives to the ongoing research, and this, in turn, contributed to a significant evolution in the integrated inspection model proposed in the thesis. The author's published work, Sinisterra et al. (2023) is linked to the two works in the thesis in the sense that 1) they are related to maintenance and optimization strategies for system or equipment in different industries, 2) they highlight the effectiveness and potential benefits of the proposed policies in terms of cost reduction, system performance improvement, and reduced downtime, 3) they contribute to the field of maintenance optimization by providing innovative strategies, mathematical frameworks, and simulation models, 4) they demonstrate the importance of considering degradation processes, inspection policies, and various optimization algorithms in developing effective maintenance strategies for different industrial systems and finally, in strong relation to the second work on this thesis, they bring the delay time as a central concept to build maintenance strategies. The two policies developed in the thesis are linked in the essence that they both deal with optimizing maintenance policies on centrifugal pumps and, where the first work deals mainly with the principal set of pumps, the second work considers both the principal set of pumps and the spare set of the same industry.

From the foregoing discussion, it is sufficed to say that it was possible to have a holistic view of the contributions that some maintenance policies (RL and opportunistic maintenance) have on a centrifugal pump in the industry of study.

1.1 OVERVIEW OF THE GENERAL PROBLEM

An equipment usually experiences aging and deterioration with time which has an impact on the finished product's quality (KURNIATI, YEH, LIN, 2015). This deteriorating process is characterized by increased rejects, reworks which can lead to system failures (SINISTERRA et al., 2023). From a modern solution to this problem, industry 4.0 aims to make connected production systems interact by using standard internet-based protocols to analyze equipment deteriorating behaviour by analyzing related data. This will help in predicting potential failure before they occur (SCHLICK et al., 2014; NAKAJIMA, 2014). The overview of the problem to be solved is hence related to the question of 1). As the centrifugal pump degrades, what decision can be made at each iteration to avoid an outright failure of the equipment? 2). If the pump's degradation is modeled with the delay-time concept, what would be the number of optimal inspections, interval of inspections, opportunity window and time for preventive maintenance for the principal and spare pump? Both questions are answered in the two works done in this thesis. Please note that the detailed problem statement for each work is given in chapter three and four.

1.2 AIM

The main aim of this thesis is to examine and propose some contributions of maintenance policy on centrifugal pumps in the iron ore process plant.

1.3 SPECIFIC OBJECTIVES

To achieve the above aim, the following specific objectives are pursued:

- To present a comprehensive literature review of maintenance policies and reinforcement learning as applied to centrifugal pumps.
- To develop an RL-based mode for optimal CBM in a centrifugal pump.
- To develop an integrated opportunistic maintenance policy on a set of principal and standby system of centrifugal pumps.

1.4 MOTIVATION

Although the literature is rich with papers and works that study the impact of various existing maintenance policies on equipment in a process plant (DROZYNER, 2020; JASIULEWICZ-KACZMAREK, SANIUK, 2018; GOUIAA-MTIBAA et al., 2018), to the best of the author’s knowledge, none has studied the impact of policies (especially RL policies) coupled with deterioration processes on centrifugal pump used in an iron ore concentrate plant. Therefore, the motivation of this thesis comes in 2 folds.

Firstly, RL has become the trending and modern technique where maintenance of single, multi-state and multi-component systems can be optimally achieved because of its robustness, large state-action space and the ability to deal with the stochastic behaviour of the system’s degradation process caused by uncertainty and external operating conditions (BARDE, YACOUT, SHIN, 2019; ZHANG, ZHU, XIE, 2021). This has brought about the motivation to develop RL algorithm for a CBM in a centrifugal pump. This would achieve the objective of optimal maintenance policy that results in minimum maintenance cost, and aids the maintenance manager in decision making.

Secondly, it is interesting to observe how the delay-time concept can be used to optimize an opportunistic maintenance for a cold standby system which results in a minimum maintenance cost.

1.5 RESEARCH METHOD

This study is an example of applied research. In each case study, the modeling procedure serves as the research methodology. The modeling procedure in the issues is unique to each case study and numerical illustration. Each of the modelling procedures tries to identify methods for incorporating the components missing from the available literature regarding maintenance policies. The collection of data is vital to study. To achieve this, the author used computer simulation techniques. For the first work, the data involved the degradation process of the centrifugal pump. This data was simulated using the variance gamma process by Monte Carlo simulation. The second work involved data related to the delay-time. The data was also simulated using the Weibull and exponential distributions. This data was assessed and proved to be consistent with real-world conditions, allowing the proposed models' solutions to be analyzed and evaluated

1.6 OUTLINE OF THE THESIS

The thesis is divided into five chapters. The first chapter is the introduction that outlines the synergy between all the problems solved, the main and specific objectives are also outlined. The knowledge gap and major contribution of each problem is well explained.

Chapter 2 presents the literature review. In this chapter, the basic concepts that link all the problems are discussed in depth. This includes the delay-time and degradation models, RL maintenance and opportunistic maintenance policies and inspection policies. Different deterioration processes such as gamma, Brownian, Variance Gamma and Markov Decision Processes are explained in depth. The relationship in the literature among these processes are also discussed. A comprehensive literature review on RL and the relevance to maintenance policy optimization is also presented.

Chapter 3 starts with a detailed description of the industry under study. The main focus of the chapter discusses the application of reinforcement learning for optimal CBM policy in a centrifugal pump.

Chapter 4 contains the second work done by the author of this thesis that involves developing an integrated opportunistic maintenance policy for a principal and cold standby centrifugal pump system using delay-time concept.

Chapter 5 presents the conclusion of the thesis which is drawn from highlighting how each of the problems discussed aid in achieving the aim of the thesis. The limitations of study and directions on future lines of research are also included.

2 LITERATURE REVIEW

This chapter presents a comprehensive literature review about the topics that are interesting in this study. Maintenance polices are discussed, the delay-time concept and the related works on the topic are analyzed. The opportunistic maintenance and inspection policies are reviewed, literature on preparedness systems is also reviewed, carefully noting the gaps in literature. Finally, the reinforcement learning and its applications to pumps is studied.

2.1 MAINTENANCE POLICIES

A maintenance policy refers to a collection of administrative, technical, and managerial measures that are implemented throughout the lifecycle of a machine. These measures guide the decision-making process of maintenance management, with the ultimate goal of maintaining specific operational standards or restoring a machine to those standards (IGI-GLOBAL, 2018).

The aforementioned restoration process involves the organization of both human and material resources, aimed at rectifying faults, wear and tear, or breakdowns in machines, devices, or facilities. This process is designed to guide maintenance management decision-making, with the ultimate objective of ensuring uninterrupted facility operation, optimal availability, safety, and quality, while simultaneously minimizing maintenance costs (HSE, 2009).

There exists 6 main broad classification of maintenance policies viz: reactive (run-to-failure), predetermined maintenance, preventive maintenance (PM) made up of time-based or condition-based maintenance (CBM), opportunistic and predictive maintenance (JONATHAN, 2021). For a comprehensive review on maintenance policies classifications, please refer to (ERBE, et al., 2005). Based on the line of thought of this research, the literature review is based on maintenance policies on preventive (time-based, opportunistic, CBM) and predictive maintenance.

2.1.2 Preventive maintenance

According to Wang and Wenbin (2012), preventive maintenance can be subdivided to 2 types which are; time-based maintenance and CBM. Opportunistic maintenance also falls under preventive maintenance. A popular kind of time-based maintenance is the delay-time based maintenance. Preventive maintenance makes use of optimal schedule of inspections and tasks to find and fix issues before they have a chance to develop into big problems (ZHAO, WANG, PENG, 2015). Due to scheduled inspections, PM tends to allow opportunities and enough lead time to ensure that the inventory is at optimal delivery. The disadvantage of PM is on extra waste and added risk (KHAIRY, PRABHAKAR, 2008). Extra waste occurs when the equipment parts are changed before they fail or become defective. The later occurs when each inspection leads to an added risk of introducing defects.

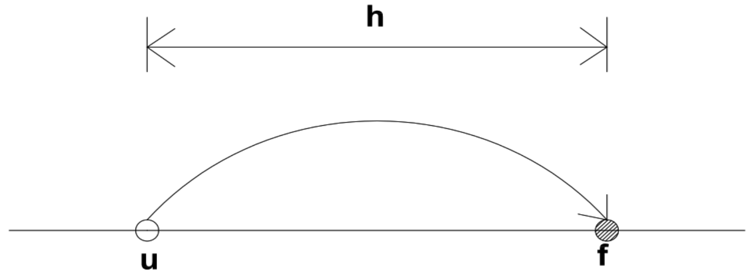
2.1.2.1 Delay-time Models

The origins of PM's delay-time models can be traced back to Christer's work in 1976, where they were first introduced in the context of building maintenance (CHRISTER, 1976). Christer and Wailer subsequently applied the aforementioned concept to industrial maintenance problems (CHRISTER, WALLER, 1984).

The delay-time concept (Figure 1) can be literarily defined as a failure process of an asset that falls from a point of new to the point that a hidden defect is detected (u), and then a defective stage, defined as delay-time (h), that is, from the point of defect identification to failure (f) (WANG, 2008). The existence of this delay time provides the opportunity for preventive maintenance to be executed to remove or rectify the identified defect before failure (WANG, WENBIN, 2012). The major challenge is to design appropriate models that optimizes inspection intervals that optimize a certain function of interest.

As stated earlier that the disadvantage of PM is the challenge of extra waste and added risk, several works on delay-time models have been done by researchers whose sole aim is to mitigate against these challenges (MAHMOUDI et al., 2017; NAZEMI, SHAHANAGHI, 2015; LIU et al., 2015; ZHAO, WANG, PENG, 2018). Apart from deploying delay-time models (DTM) to mitigate against the effect of waste and risk, DTMs have been applied to both single and multi-component systems. Delay-time models have also been found useful in modeling inspection policies for protection systems, as demonstrated in (CAVALCANTE, SCARF, BERRADE, 2019), where inspection outcomes provide imperfect information on the system's state. The novelty of their study lies in investigating the effect of imperfect inspection probabilities on the efficacy of inspection, and the results indicate that preventive replacement is an effective approach to mitigate the impact of low-quality inspection, and inspection remains cost-effective provided the probabilities of imperfect inspection are not too large. Another study, Berrade et al. (2013), explores the use of periodic inspections to check the system's state, where inspections are subject to errors. Other studies, such as Santos, Cavalcante and Ribeiro (2021) on environmental sustainability Rodrigues, Cavalcante and Alberti (2023) on multicriteria modeling environments, demonstrate the diversity of industrial applications of delay-time models. These diverse applications of delay-time models suggest an interesting trend in the potential impact of such models on various industrial environments.

Figure 1 - Delay-time concept



Source: adapted from Werbinska-Wojciechowska (2019)

2.1.2.1.1 Delay-time for Single-component systems

A single-component system is a system that comprises of a unit or set of unit items whereby they are all subjected to the same failure process (BARLOW, HUNTER, 1961). Defining a single-component system is associated with the way the system is seen. This means that even though a complex system comprises of a component and its socket, whereby both provide an essential function such that if the component fails, the system fails, it is still a single-component system. A pure single-component system is therefore rare, many systems are complex systems with many components. Real-life systems are usually reduced to single-component systems so as to simplify the PM modelling process. Wang, Wang and Peng (2017) presented a 2-phase inspection schedule and an age-based replacement policy for a single plant item contingent on a 3-stage degradation process. Their line of thought was that multi-phase inspection schedule may be more applicable to a multi-stage deteriorating item, therefore their work encompasses the idea of a single-component system observing a multi-stage deterioration. The major contribution of their work is that the maintenance of the item could be delayed until when the time to the age-based replacement is greater than a threshold. The critic of their work is the assumption that, from the second inspection, all subsequent inspection intervals were assumed to be constant. Relaxing this assumption would result in a truly multi-phase inspection model. In the work of Li et al. (2015), the delay-time concept coupled with accumulative age is presented for a single-component system under the assumptions that failure modes are independent of each other, maintenance is imperfect, and all kinds of defects are dealt with in each maintenance task. The demerit of their work is that independence of the failure modes may not fully portray the ideal real-life case. Zhao, Liu and Peng (2018) presented a periodic inspection policy for a single-component system based on a 3-stage failure process. Their major contribution is the introduction of the human factor into the quality of repair activities. The common practice in the foregoing mentioned works is that the maintenance policies are being optimized by minimizing the expected cost per unit time. In Scarf et al. (2009), a hybrid maintenance policy was examined for a single component in a heterogeneous population using the delay-time model. This study highlights the potential of delay-time models for hybrid maintenance policies, such as combining inspection and replacement policies. The results indicate that the hybrid policy yielded significant cost savings compared to standard age-based replacement and pure inspection policies. A recent work by SINISTERRA et al. (2023) proposed a model that integrates the schedule of a sequence of resumable jobs and inspection policy in a single-component system using the delay-time concept.

Most works in the literature assume a 3-stage degradation process i.e., from new to the arrival of defect, the delay-time and then the delay-time until inspection is performed or failure occurs (ZHAO, LIU, PENG, 2018; REDMOND et al., 1997; SHEN et al., 2021). This enables the model to represent real-life scenarios. The 3-stage failure process is achieved by further dividing the delay time into minor and severe defect stages which can provide more maintenance decisions based on different defects (WANG, ZHAO, PENG, 2014; SANTOS et al., 2023).

2.1.2.1.2 Delay-time for multi-component systems

A multi-component system is one in which multiple maintenance decisions are to be made for each of its component. Delay-time models based on multi-component systems have been explored (CHRISTER, WALLER, 1984; LI, FANG, SHI, 2021; KANG, CATAL, TEKINERDOGAN, 2021; PENG et al., 2022). The complexity of multi-component system failure process arises from the fact that each component will have its own unique failure mode which will give rise to its unique failure mechanism as well as a failure process (LI et al. 2015). Failure arrivals are usually modelled in homogenous Poisson process (HPP) or non-homogenous Poisson process (NHPP) (DOYEN, GAUDOIN, 2004; HONGZHOU, HOANG, 2006). NHPP are known to provide a good first-order model to the real-world problems (HAROLD, 2008; ASCHER, 1992). When the number of components is large, a common practice is to model the inspection and failure process using a stochastic point process (HPP or NHPP) for defects arrival and a common delay-time distribution for the deviation between the arrival and failure of all defects (WENBIN, DRAGAN, MICHAEL, 2010).

In the work of Christer and Wang (1995), a model of multi-component system subjected to both planned inspection and opportunity inspection at failure is constructed based on the delay-time concept. Their work however, considered the case of perfect inspections. The model was tested on maintenance data on infusion pumps used in a local hospital. Wenbin, Dragan and Michael (2010) proposed a multi-component-based delay-time model which considers several components individually but at the same time to form a subsystem. The model offered maintenance managers a useful tool for determining the optimal plant inspection intervals. The major contribution was found in the fact that they considered a case of more than one failure mode of a component, however, the inspection process was assumed to be perfect. Wang and Christer (2003) proposed 3 algorithms for a multi-component system based on the delay-time concept. The first algorithm was developed for obtaining the system replacement time if the defect arrival process is non-homogenous. The second algorithm determined the non-constant optimal inspection intervals and the third algorithm was a numerical algorithm for solving an integral equation arising within the model in the case of opportunistic inspection at failures. The task at hand presented a conventional multi-decision problem, characterized by a substantial number of decision variables. To address this, the authors proposed an algorithmic approach that employed recursive procedures to ascertain replacement times, thereby reducing the number of decision variables and simplifying the problem. The proposed algorithms demonstrated efficacy in optimizing maintenance performance in multi-component systems subject to non-homogeneous deterioration processes. The critic of their work is inherent in the assumption that defects are independent. It should be noted that failure of a component may lead to the failure of another component resident in the same multi-component system. They also assumed that both failure and inspection downtimes are negligible compared to the life-time of the system. The advantage of deploying DTM in multi-component system is that, during inspections, it may be possible to inspect other components of the system and remove identified defects as part of the repair (CHRISTER, WANG, 1995; WENBIN, DRAGAN, MICHAEL, 2010; WANG, CHRISTER, 2003).

It can be seen that from the above referenced works, the main aim of DTM is to serve as a PM model that optimizes inspection times. Therefore, it is sufficed to say that DTM is linked with inspection policies.

2.1.3 Condition-based Maintenance

Condition-based maintenance (CBM) was first introduced by Rio Grande railway company in the late 1940s and was initially called predictive maintenance (PRAJAPATI, BECHTEL, GANESAN, 2012). Several authors have defined the term. CBM was defined by Bengstson (2004) as a preventive maintenance based on parameter monitoring and the subsequent actions. This definition is in line with what Prajapati, Bechtel and Ganesan (2012) called it. It is also referred to as on-condition maintenance. According to US air force Prajapati, Bechtel and Ganesan (2012), CBM can be defined as a set of maintenance processes and capabilities derived from real-time assessment of weapon system condition obtained from embedded sensors and or external test and measurements using portable equipment. With regards to this definition, one can see that with the emerging technologies such as Radio Frequency Identification (RFID) and sensor systems, it has become easy to monitor the performance of equipment in real-time by gathering and analyzing data. Also, Michael (2001) defined CBM as a maintenance philosophy that involves the prediction of evolving failures and Remaining Useful Life (RUL) to optimally determine when to perform maintenance, it can be seen here that he extended the definition of CBM to cover not only the engineering field. CBM is defined by Caballe et al. (2015) as an extended version of predictive maintenance where automatic triggering alarms are activated before obtaining any breakdown. This ascertains the fact that CBM can also be treated as a predictive maintenance since it can be deployed for failure prediction (MICHAEL, 2001). Lastly in the definition, Dieulle et al. (2002) defined CBM as a maintenance strategy that collects and assesses real-time information, and recommends maintenance decisions based on the current condition of the system.

Some interesting key points can be deduced from the aforementioned definitions; CBM can be seen as a tool for predictive/preventive maintenance, CBM is deployed in the presence of sensors monitoring devices and according to Shin and Jun (2015), CBM makes a diagnosis of an asset status based on wire or wireless monitored data, predicts the assets abnormality, and executes suitable maintenance actions such as repair and replacement before serious problem happens.

Several works have attempted to buttress the importance of CBM in modern engineering maintenance. For example, Shin and Jun (2015) leveraged on the advent of emerging ICT to improve the efficiency of asset operations by implementing a CBM approach to make diagnosis of the asset status. This predicted the asset's abnormality, executes maintenance actions, repairs and replacement before serious problems happen. From their work, it showed that CBM focuses on the prediction of degradation process of the asset, which is based on the assumption that most abnormalities do not occur instantaneously (FU et al., 2004). Ana et al. (2018) extended CBM approaches by considering machine learning and augmented reality technologies to support maintenance technicians during the maintenance interventions by providing a guided intelligent decision support articulated by the use of human-machine interaction technologies. Their work aligned with industry 4.0 principles (ACHOUCH et al., 2022). Industry 4.0 provides that CBM predictive maintenance can be achieved by applying sensor technology in monitoring and they must be effective at predicting failures and also provide sufficient warning time for upcoming maintenance.

There have been several models developed for CBM usage. These models range from those that can be used in discrete time such as Markov, Harrou, Sun and Madakyaru (2016) or semi-Markov decision processes Moura et al. (2008) to continuous time models and lately, models concerning data mining, data processing and artificial intelligence (AI). Data mining model includes such models as Bayesian models Ly et al. (2009), logical analysis of data Mortada, Yacout and Lakis (2011), genetic algorithm and fuzzy models (MORTADA et al., 2012). AI models is inclusive of neural networks Ogaji and Singh (2003), deep learning and reinforcement, Thais et al. (2022) learning to mention a few. All the above listed models are rarely used in isolation since their integration usually provides more advantageous results (LIU, DONG, PENG, 2012). For example, the genetic algorithm has been well used in combination with Monte-Carlo simulation for risk management associated with strategy selection (MARZIO, ENRICO, LUCA, 2002; CAMCI, 2009). Another example is found in the work of Moura et al. (2015) where the authors proposed a coupling between a risk-based inspection methodology and multi-objective genetic algorithm for defining efficient inspection programs. In selecting an appropriate model, the type of model to use should be dependent on a proper comprehension of the degradation process of the system (QUATRINI et al., 2020). The degradation process describes the progressive deterioration of sub-components over time, which serves as a crucial input for the development of a reliable Condition-

Based Maintenance (CBM) algorithm, also known as the intervention model (FRANGOPOL, KALLEN, NOORTWIJK, 2004; KALLEN, 2007). As such, an effective CBM policy should encompass both a degradation model and an intervention model. Some other examples of CBM models are found in the work of Arismendi, Barros and Grall (2021) where they explored the application of a piecewise deterministic Markov process to encompass different modelling assumptions as non-negligible maintenance delays and inspection-based condition monitoring. This model employed a discrete-state stochastic deterioration. It allowed the study of problems in which condition monitoring is not continuous but inspection-based and there is an inherent delay for performing maintenance actions. Also, Ma et al. (2019) built a CBM based Random fuzzy accelerated degradation model and based their assumption on imperfect maintenance.

The benefits of CBM include amongst others, reduced maintenance and logistics costs, improved equipment availability and protection against failure of mission critical equipment. Even with the aforementioned advantages enlisted above and in several works by researchers on CBM, some challenges of its adoption still exist. Scarf (2007) stated that CBM can be expensive to implement and return on investment in its technology are not guaranteed. Also, on the issue of cost, there exists the costs associated with integration of an intelligent system with the existing systems as well as with the reluctance of change from the human players. CBM has limitation in working in an integrated manner for collaboration with other stakeholders (SUN et al., 2012). Even with the effectiveness of monitoring historical data, modelling, simulations and failure probabilities to predict fault system deterioration and their useful life, certain unexpected situations may arise that are hard to predict. Despite the challenges mentioned earlier, Condition-Based Maintenance (CBM) continues to exert a significant influence in the present era of Industry 4.0. This is largely attributed to its reliance on novel technologies and data-centric methodologies that were previously unavailable in the earlier industrial epoch. CBM confers notable benefits over conventional maintenance strategies and has gained increasing prominence as enterprises strive to optimize their operations in the prevailing context (TEIXEIRA, LOPES, BRAGA, 2020; ZONTA et al., 2020; SILVESTRI, 2020; RAHMAN ET AL., 2020).

2.1.4 Opportunity Maintenance

Opportunity maintenance (OM) is defined as a type of preventive maintenance strategy in which maintenance activities are performed whenever an opportunity arises, rather than according to a predetermined schedule. OM was introduced by Radner and Jorgenson (1963). It was first applied as a concept of dependency of the components as equipment in a system, i.e., maintenance is to be performed on a given part at a given time depending on the state of the rest of the system. It is the practice of taking an available opportunity to perform necessary maintenance tasks on a system or equipment. This type of maintenance often occurs when a system is already scheduled to be offline or in a dormant state, allowing maintenance workers to perform necessary tasks on other components of the system without causing any disruptions to the main system's operation (BAKHTIARY, ZAKERI, MOHAMMADZADEH, 2021). Opportunistic maintenance is often used to minimize downtime and ensure that systems and equipment remain in good working condition (ZHANG, YANG, 2021).

There is a significant amount of literature on opportunistic maintenance and its benefits for industries. Many studies have shown that opportunistic maintenance can help reduce downtime and improve the overall performance of systems and equipment (XIA et al., 2021; ZHANG, TEEA, 2019; WANG, MAKIS, ZHAO, 2019; MOHAMED-SALAH, DAOUD, ALI, 1999). One study by Ab-Samat and Kamaruddin (2014) found out that opportunistic maintenance can help reduce downtime by up to 30% while also improving the overall reliability of systems and equipment. That study is in agreement with Sherwin (1999) who concluded in his work that OM is mostly useful and easily practiced in continuously run system that have high cost-rate of downtime or failure. Another study by Sarker and Faiz (2016) found out that opportunistic maintenance can help industries reduce maintenance costs by up to 40%, while also improving the overall performance of systems. Kang and Guedes Soares (2020) proposed an OM policy for offshore wind farms. They considered imperfect maintenance and the weather widow effect. The wind turbine is viewed as a multi-component system, a failure of one component provides an opportunity to implement PM on the other. The most critical component in their work is the gearbox, they found out that by performing repairs on two 2 gearboxes together, the maintenance frequency was reduced by 15%.

In a literature review paper by Ab-Samat and Kamaruddin (2014) they agreed that OM is developed based on a combination of age replacement policy and block replacement policy. It should be noted that OM is better utilized in a multi-component environment than age replacement policy because if age replacement policy is considered in a multi-component setting, each component will suffer preventive replacement at different times. This creates a very complex maintenance problem making a myriad occasion of maintenance activities needing to be conducted. In the case of block replacement policies applied in multi-component environment, the downside is that there is a high possibility that newly replaced components will need to be replaced again whenever maintenance is due for the block (WANG, 2001).

With the aforementioned discussions, several advantages of deploying OM in an industry can be summarized, such as; it saves setup costs Cui and Li (2006), guarantees the expected performance of the system Levrat, Thomas and Lung (2008), it optimizes maintenance activities and decision making Laggoune, Chateauneuf and Aissani (2009), and it improves equipment reliability and extend its lifetime (ZHOU, XI, LEE, 2009). It has been shown that inspections that are performed opportunistically may offer an economic advantage over scheduled maintenance (SCARF et al., 2009). The principle of OM posits that during maintenance of a failed component, other maintenance-critical components with a propensity to fail imminently should also undergo inspection or preventive replacement. A key challenge in implementing this principle is the identification of the maintenance-critical component, as replacing a good component incurs unnecessary expenses on maintenance and spare parts (AB-SAMAT, KAMARUDDIN, 2014). This thesis surmounts this challenge by leveraging expert knowledge to pinpoint the critical component within the machine system.

2.1.5 Inspection Policies and Opportunistic Inspection Policies

Inspection policy has to do with the determination of inspection intervals of an equipment or group of equipment. This is one of the key decisions of a maintenance manager (CHRISTER, 1999). It is sometimes developed as a periodic inspection, known as inspection per calendar (TANG et al., 2013). An optimal inspection policy is a sequence of inspection times which minimizes the average cost per inspection cycle relative to some cost model (MUNFORD, 1981). For most systems, whether single or multi-component, failures are not detected immediately they occur. These are noticed in cases where failure is not catastrophic and an inspection is required to reveal the fault

(KAIO et al., 1989). Establishing an optimal inspection policy becomes a necessity. The idea is to make sure that the system is ready whenever it is required. If too many inspections are executed, failure is detected more quickly, but at a high inspection cost. Likewise, if few inspections are executed, the interval between the failure and its detection increases and a high cost of failure is incurred. The optimal inspection policy therefore minimizes the total expected cost composed of cost for inspection and system failure (MUNFORD, 1977; TADIKAMALLA, 1979; NAKAGAWA, YASUI, 1980).

Inspection policy by Barlow, Hunters and Proschant (1963) is the most famous in which a one-unit system is considered. The disadvantage of this policy is its complexity and difficulty in implementation due to the need for trial and error in determining the initial inspection time, as well as dealing with the constraints of failure time. This can make it challenging to execute in practice. Because of this, several inspection policies have been proposed (NAKAGAWA, 2005; KAIO et al., 1989; NAKAGAWA, MIZUTANI, CHEN, 2010; TRUONG-BA et al., 2021; MIZUTANI, ZHAO, NAKAGAWA, 2022). Inspection policies are either; periodic inspection Alaswas and Xiang (2017), scheduled inspection Li and Pham (2005), Remaining useful life-based inspection Do, Levrat and Lung (2015) and continuous inspection (HAITAO, ELSAYED, LING-YAU, 2016). The concept of opportunistic inspection policy pertains to a methodical approach that entails undertaking collection, investigation, and pre-planning activities to generate a set of maintenance tasks that can be implemented when opportunities arise (DAY, GEORGE, 1981). Thus, the development of a robust opportunistic inspection policy holds paramount importance, as it enables managers to make informed decisions when opportunities arise (CAVALCANTE, LOPES, 2014). In this thesis, the major contribution in this regard is to develop an opportunistic inspection policy for a standby system, taking as opportunities, the actions in a principal system not assisted by the standby system. The work conducted by Cavalcante and Lopes (2014), underscores the significance of implementing an opportunistic inspection policy. Specifically, the researchers developed an opportunistic maintenance policy to aid in making maintenance decisions regarding an emergency system installed in a health facility that provides electricity in the event of primary system failure. The policy was designed with the assumption that failures within the emergency system are not readily observable and may lead to detrimental outcomes for the health unit. This formed the underlying motivation behind their study. Cavalcante, Lopes and Scarf (2018) conducted a study that involved modeling the impact of opportunities on a hybrid and replacement policy. The policy in question comprised of two distinct phases, namely, an initial inspection phase that involved replacing the system in the event of any detected defects, and a wear-out phase that culminated in replacement despite the state (good or defective). The findings of their study indicated that the incorporation of opportunities in policy extension led to increased cost-effectiveness compared to age-based inspection or preventive replacement. Moreover, the study underscored the significance of the delay-time concept in modeling opportunity inspection policies. Notably, the delay-time concept has been employed successfully over the years in modeling opportunistic inspection policies by researchers (BERRADE, SCARF, CAVALCANTE, 2015; WANG, CHRISTER, 2003). Using the delay-time, one can take advantage of the window of opportunity generated by it. Therefore, it is right to say that the delay-time concept can create a window of opportunity that can be utilized to establish an effective inspection policy (SINISTERRA et al., 2023). Latest research by Melo et al. (2022) entails the development of a maintenance policy featuring a fixed period structure that integrates elements of periodic and opportunistic replacement for a remote system. The study's novelty lies in the incorporation of key uncertainties such as early, cost-effective replacements, defaulting, and the varying quality of maintenance interventions. The research findings reveal that the utilization of opportunities can significantly impact the cost-rate of the optimal policy. The researchers also established that maintenance planning should remain flexible, particularly when external factors beyond a maintenance manager's control impact maintenance effectiveness. Additionally, they demonstrated the usefulness of capitalizing on opportunities during lockdown situations, particularly for equipment situated in remote locations. The crucial insights derived from the aforementioned studies highlight that an adeptly designed opportunistic inspection policy could streamline maintenance planning (CAVALCANTE, LOPES, SCARF, 2018). This is due to the fact that opportunities for replacements may arise with fewer uncertainties than scheduled or age-based replacements, rendering scheduled inspections and preventive replacements less necessary. Even if a company has to adopt scheduled preventive actions, opportunities can still be capitalized on in the interim (ROMMERT, ERIC, 1991). In general, opportunity inspection policies are deemed more pertinent as they enable more efficient resource utilization, resulting in heightened cost-effectiveness (LI et al., 2020).

2.1.6 Preparedness System

The discussion on OM cannot be exhausted without discussing what a preparedness system is and how it can benefit from opportunity maintenance. A preparedness system is a system that is used in special situations. Example of preparedness system are: standby, protection, alarm defense and etc., Specifically, a standby system is a backup system that is used to provide continuity of function in the event of a failure or disruption of the primary system. In a situation when the standby system may be in either the good or failed state, the purpose of inspection is to establish if the system would operate in the event of a demand for its function (ZHAO, NAKAGAWA, 2015). Therefore, OM inspections can be deployed on standby systems so as to increase their reliability. OM policies help the manager to make decisions with regards to the standby system in the occurrence of an opportunity (CAVALCANTE, LOPES, 2014). Preparedness systems are commonly used in critical infrastructures and other applications where reliability is of the utmost importance. Such applications are found in military defense systems, medical equipment, protection systems (MCCALL, JORGENSON, 1967). In some critical multi-component systems such as; aircrafts, the stochastic dependency of components to one another can be used to plan OM according to the component's interactions (AB-SAMAT, KAMARUDDIN, 2014). In general, a preparedness system is designed to take over the functions of the primary system at a moment's notice, ensuring the overall system continues to operate smoothly and without interruption.

There are basically three groups of standby systems in maintenance engineering, they are enlisted as:

a. Hot standby: The hot standby backup system operates continuously and collaboratively with the primary system to deliver its functions. As a result, the failure rate of the backup system remains equivalent to its operational failure rate (ZHANG, XIE, HORIGOME, 2006). This configuration compromises the reliability of the standby unit but reduces its downtime, ultimately increasing the system's availability. The power industry provides an excellent illustration of this, where hot standby systems are deployed to prevent downtime in the event of a critical component failure (RIZWAN, KHUANA, TANEJA, 2010). Other examples of such systems can be found in audio/visual switches, network printers, network servers, computers, and hard drives (MARGARET, 2014; RIZWAN, KHUANA, TANEJA, 2010; PATOWARY, PANDA, DEKA, 2019).

b. Warm standby: A warm standby system operates with the backup system running at low power, enabling rapid deployment if necessary. As an intermediate state, this configuration results in a standby component failure rate between that of a cold standby and hot standby (ZHANG, XIE, HORIGOME, 2006). It is frequently employed in scenarios where a fast switch-over time from the failed component to the standby component is critical, such as in surgery with a shadow-less lamp. In such cases, the standby component is maintained in a low-charging state with a low and positive failure rate to allow immediate activation once the primary component fails (HAZRA, NANDA, 2015). Other examples demonstrating its use are found in the works of (JIA et al., 2022; JIA et al, 2017; LEVITIN, XING, LUO, 2019).
c. Cold standby: In this scenario, the backup system remains inactive and must be initiated manually in the event of a primary system failure or disruption. Consequently, the standby unit has a zero-failure rate and is incapable of failing while in standby mode Lin et al. (2023) thereby preserving its reliability. However, this configuration incurs longer downtime than hot standby since the standby unit must be powered up and brought online to a functional state (NI, 2022). As such, it is primarily utilized in settings that prioritize energy conservation (ZHANG, ZHANG, FANG, 2020). Other examples exist (BEHBOUDI et al., 2021; WANG, XIONG, XIE, 2016; WANG et al., 2018; LEVITIN, FINKELSTEIN, DAI, 2020).

The cold standby seems to be the most popular area of research. This is evident because most industrial standby systems are usually dormant until called upon to carry out the auxiliary function. Works that studied cold standby systems include, in Jia and Wu (2009), they presented the model of the expected run cost per unit time for a cold-standby system composed of 2 identical components with perfect switching. They allowed the assumption that for cold-standby system, there exists a waiting time from the failure of the component to the start of repair, and real repair time which is the time between the start to repair and the completion of repair. Lu et al. (2012) studied a one-out-of-two cold standby system. The failure of the 2 components is modelled according to the delay-time concept. The inspection interval is optimized because the repair shop can only accommodate a single spare system at a given time. Qi and Zhou (2019) developed a novel preventive maintenance model for a cold standby system subjected to random and deterioration failures. Results showed that PM plays a greater role than mean time to system failure in promoting the system availability of a cold standby system. They confirmed that the deterioration of a cold standby system can lead to its failure when demand arrives, therefore, it is imperative to investigate this. Berrade, Scarf and Cavalcante (2015) considered an inspection and preventive replacement policy for a cold standby system. They considered imperfect inspections and a case of false positives and negatives. Their primary contribution was to measure the effect of quality of maintenance on the standby system.

In summary for studies related to cold standby systems, it is noted that cold standby systems experience hidden failures. They are subject to false positives and negatives because of their redundant nature, and they can deteriorate naturally due to age. Therefore, these systems must undergo inspections at regular intervals to ensure their high availability (APOSTOLAKIS, 1977).

2.1.7 Other works on preparedness systems

Calvalcante, Scarf and Almeida (2011) considered an inspection policy for a single component preparedness system. This component comes from a heterogenous population. A heterogenous population allows one to inspect the impact of weak and strong components on inspection policies for a preparedness system (SCARF et al., 2009). Because a preparedness system must be available on-demand, it should undergo sequence of inspections. They therefore studied a 2-phase inspection policy. This policy anticipates a high inspection frequency in early life and low inspection frequency in later life. The decision criteria are availability, total cost per time, and maintenance cost per time, the decision variables are number of inspections until replacement time (also known as the inspection interval) and the time units taken. They deployed the delay-time concept to model the 3 component states (good, degraded and failed states). Their innovation in comparison to other works is noted in the assumption that failure is not detected as soon as it occurs, rather, the component is assumed to be in a dormant, failed state. With this assumption, they were able to show that inspection and replacement have different roles for improving system performance. For inspection, pure inspection for a component in defective state results in high availability since the component may most likely not fail. For replacement, replacement may not be planned because when a defective state is observed at inspection, that inspection will anticipate failure. They investigated the numerical case on a valve in a natural gas supply network. Results showed a 5% cost savings for the 2-phase inspection policy over the single-phase policy.

Neelakanteswara and Bhadury (2000) proposed an opportunity maintenance based on the classification of opportunities for a multi-equipment system where each of its components and subsystems are connected in series. In their work, five equipment (pulverizers) are required for full capacity operation. One serves as a standby. If one or more pulverizers is down, the efficiency of the system is reduced. The pulverizer has many subsystems connected in series. Data collected includes downtime for each of the equipment. The data showed the major equipment responsible for incessant shutdown. This agrees with the postulation of Ab-Samat and Kamaruddin (2014) and Kang and Guedes Soares (2020) which states that, in order to improve the overall condition of a system, efforts should be directed to reduce the frequent failures of the critical subsystem(s). In their results, they evaluated various OM policies using simulation modelling and found out that their policy performed better than existing OM policies.

Zhang et al. (2017) proposed an OM for wind turbines considering imperfect maintenance schedule that is based on reliability. An interesting aspect in their work is the comparison of maintenance strategy with and without the use of opportunity maintenance. The average maintenance cost rate was used as the criteria for comparison and it was established that deploying OM performed better. Their results demonstrate the impact that various maintenance costs have on the economic benefit of OM strategy. However, their work did not take into cognizance the total time spent on maintenance for the consideration of the lifetime of the equipment.

There have been the questions of what thresholds should be used for opportunity maintenance for preparedness systems, the popular thresholds are; degradation or risk rate and the operation time (DO et al., 2015; LIAO, PAN and XI, 2010; VAN et al., 2013). The delay-time has widely been used in literature to model these thresholds. For example, Liu et al. (2021) used delay-time to address and estimate the multi-stage deterioration process to determine multi-level maintenance actions for multi-component systems in series. Zhang (2019), Scarf, Cavalcante and Lopes (2019), Lu et al. (2012) and Yang et al. (2016) all made use of the delay-time concept to model the degradation of the equipment in their case study. However, Zhang (2019) improved on existing delay-time model that assumes that the normal and defective stages are independent. They considered the dependence between the normal and defective stages which is reflected in the fact that they share the same external shock process.

In summary, it can be deduced that the common planning approaches for multi-component systems include block, group and OM policies. However, from the preceding analysis, OM policies are better suited for multi-component systems (ZHANG, ZENG, 2015). It is pertinent to state that, the industrial benefits of OM far outweigh that of PM and CM in a high-volume, multi-component production firm. In order to predict the impact of OM on system performance, a methodology was developed by Colledani, Magnanini and Tolio (2018) that estimated gains that can be generated by exploiting OM windows to perform PM tasks during production. Therefore, the analyzed literature on opportunistic maintenance suggests that this approach can provide significant benefits for organizations, including reduced downtime and improved reliability and performance of systems and equipment.

2.2 MACHINE LEARNING ALGORITHMS

Predictive maintenance (PdM) has evolved from ordinary visual inspection to automated methods using advanced signal processing techniques based on machine learning (ML) (HASHEMIAN, 2011). Because of the abundance of data and its availability, machine learning approaches are viably used in predictive maintenance (PAOLANTI, 2017). Machine learning uses items from basic data processing, diagnostics and prognostics for predictive maintenance implementation. ML methods have emerged as a promising tool in PdM applications to prevent failures in equipment that make up the production lines in the factory floor (CARVALHO et al., 2019). Three approaches are distinguished in CBM, data-driven, model-based and hybrid approach. The data-driven approach, also called the data mining approach is the ML focus. The idea is to use historical data to learn the behaviour of the system.

ML algorithms can be broadly classified into 2 main groups, supervised and unsupervised learning. In supervised learning, the information on the occurrence of failures is present in the modelling dataset. Supervised learning requires labelled and output data during the training phase of the ML iterations. This training data is often labelled by the data scientist in the preparation phase, before being used to train and test the model. Once the model has learned the relationship between the input and output data, it can be used to classify new and unseen datasets and predict outcomes. Examples of situations where supervised ML are used are in classification and regression problems. Unsupervised learning, on the other hand, is the training of models on raw and unlabeled data. It is often used to identify patterns and trends in raw datasets, or to cluster similar data into specific number of groups. Situation examples include; clustering, association and anomaly detection problems. Although supervised ML models tend to give more accurate predictions, most real-life datasets come without labels.

Carvalho et al. (2019) prepared a comprehensive systematic literature review on ML algorithms applied to PdM, showing which are being explored in the field and the performance of the current state-of-the-art ML techniques. They found out that the most employed ML algorithm are random forest, artificial neural networks (ANN), support vector machines (SVM) and k-means.

Random forest (RF) is a collection of decision trees, it is a supervised learning algorithm for both classification and regression tasks. RF generates decision trees randomly, they avoid overfitting better than decision trees because they work with random subsets of features and build smaller trees from such subsets (BREIMAN, 2001; BIAU, SCORNET, 2016). In Prytz et al. (2015), RF was used as a classification algorithm, the work developed a generic method for predicting repairs to various components of commercial vehicles. Paolanti et al. (2018) describes a RF approach for PdM. Data was collected by various sensors; machine PLCs and communication protocols were made available to a data analysis tool on the Azure cloud architecture. The idea of the work was to predict the different machine states with high accuracy. Other high quality PdM works based on the RF algorithm can be found in (DOS SANTOS et al., 2017; KULKARNI et al., 2018). RF has shown good performance of maintenance predictions when the number of variables considered is larger than the number of samples. It can also reduce variation and increase generalization. The demerit is that it is a complex algorithm and it requires more computational time when compared to other ML techniques.

ANN is based on intelligent computational techniques which is inspired by biological neurons (BISWAL, SABAREESH, 2015). They have a relatively simple deployment due to several processing units comprising of nodes. The intelligence of ANNs comes from the interactions between these nodes. ANNs have been applied in the area of predictive control as classification models (SHIN, JUN, KIM, 2018; DUER, 2020; KANG, CATAL, TEKINERDOGAN, 2021; SAHU, PALEI, 2020). An example is found in Safoklov et al. (2022) that presented a designed model of maintenance repair and overhaul of an aircraft with a predictive maintenance unit. ANN was deployed as the maintenance tool in the work. The algorithm provided a controlled monitoring of aircraft components in order to avoid unscheduled maintenance and repair. In Daniyan et al. (2020), an ANN system was designed to train maintenance personnel on how to monitor and analyze data from the Internet of Things (IoT) and other sources to predict the state and potential failure of a railcar wheel bearing. Other maintenance works where ANNs have been utilized include in prediction of remaining useful life (LIU, LI, WANG, 2021; TIAN, 2012, BEN ALI et al., 2015). ANN advantages lie in that it is not based on expert knowledge to make decisions, they suffer no degradation even if data is inconsistent and they are easily reusable. Disadvantages include the fact that training can be time consuming, they require huge amount of data and are usually black box models.

SVM is widely used for performing classification and regression tasks. It is known to exhibit high accuracy and has a high precision in the separation of different classes of data. This leads to the accuracy of knowing the best point for separating classes of data (SUSTO, BEGHI, 2016). It is a supervised ML algorithm that performs regression analysis and pattern recognition. SVMs are used in identifying and diagnosing failures Praveenkumar et al. (2014) and Tuerxun et al. (2021), predictive control Li et al. (2014), Kang et al. (2020), Wang et al. (2020) and Gordon et al. (2020) and RUL (YAN et al., 2020; LI, FANG, SHI, 2021). Even with the high precision classification ability of SVMs, it has some disadvantages. These are; it finds difficulty in choosing a good kernel function for its model making the training time grow as the number of samples increases. It is also difficult to understand and interpret (a common disadvantage of most ML algorithms).

In contrast to the above-mentioned ML algorithm used in predictive maintenance, K-means is a clustering algorithm that utilizes an unsupervised strategy to determine a set of clusters (DHALMAHAPATRA et al., 2019). The aim is to group data in such a way that each group is identified by the distance to their reference point. The K symbol represents the number of clusters or partitions possible. The K-means is easy to implement, provides good performance and handles large data sets (as long as the number of clusters k is small). It also has the advantage of minimizing interclass variance and increases the extra class distance. Most application of K-means in PdM is in the area of analysis, that is, to identify the characterization of each cluster class. Works in that regards include; Yoo et al. (2022), where K-means was used to identify error data in acceleration sensor data of a wafer transfer robot in a production firm. Failure mode clustering work (CHABANE, ADJERID, MEDDOUR, 2022). Health classification of hydraulic system and clustering the failure characteristics for predicting equipment failure (NOVA RIANTAMA et al., 2020). Challenges inherent in k-means usage involves difficulty in determining the number of clusters required. Random seed use poses differentials in final results. The algorithm can also be scale sensitive, that is, data normalization will cause changes in the results.

The 3 commonest ML methods used for PdM (ANN, SVM, RF) are of supervised learning. These methods come with their limitations. Therefore, research is shifting towards the use of a class of ML architecture known as Reinforcement Learning (RL). Though ML supervised learning algorithms converge faster than RL, RLs are known to perform critical decision making. Because of their capacity to create a simulation of an entire system, it becomes possible for an intelligent agent to test new actions or decisions, change course when failures occur, while building on successes (MAHMOODZADEH et al., 2020). Reinforcement learning algorithms have been used in a wide variety of application such as industrial robotic, business planning, healthcare diagnosis, natural language processing and maintenance planning (KOPRINKOVA-HRISTOVA, 2014; OROOJENI et al., 2015). These algorithms are useful to solve problems subject to uncertainty without specific instructions, determining the best course of actions that should be taken in order to optimize the long-term performance of the system.

2.3 REINFORCEMENT LEARNING ALGORITHMS

Reinforcement learning (RL) which was derived from neutral stimulus and response is basically a branch of machine learning algorithm which has become popular because it addresses the problem of sequential decision making (SUTTON, BARTO, 2018; FRANÇOIS-LAVET et al., 2018). It is an area of machine learning that explains how an agent might act in an environment in order to maximize some given reward. The agent either obtains a reward or gets a punishment from the action, as the case may be. Reinforcement learning algorithms study the behavior of subjects in such environments and learn to optimize that behavior, and they usually train their policy through sampling transitions in the state and action space with either experiments or simulations (HUANG, CHANG, ARINEZ, 2020). It is based on the reward/punishment system of trial-and-error learning founded on animal psychology (NIAN, LIU, HAUNG, 2020). Actions resulting in good outcomes are likely to be repeated, while actions with bad outcomes are muted.

Reinforcement learning methods are generally classified into how the agent behaves in the environment. There are 3 basic classifications:

Value-based: The agent learns the state or state-action value. It acts by choosing the best action in the state.

Policy-based: agent learns directly the stochastic policy function that maps state to action. It acts by sampling policy.

Actor-critic: This is a hybrid of both value and policy-based methods. An ‘actor’ updates the policy distribution in the direction suggested by the critic and the ‘critic’ estimates the value function.

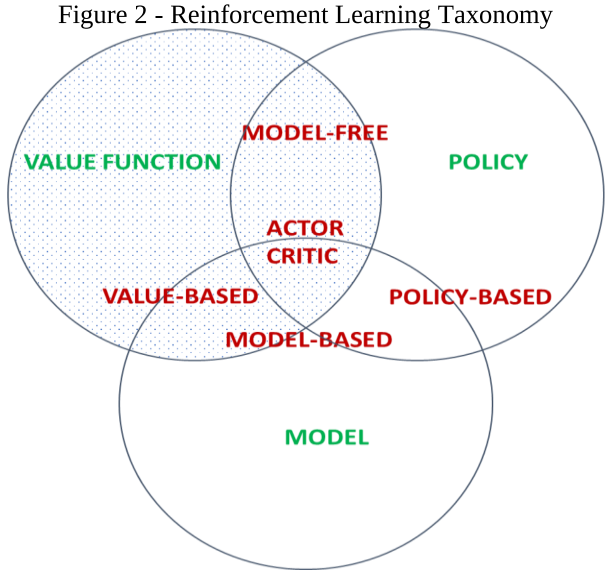
The classification of RL methods is also according to the necessity of a model:

Model-based: model-based methods learn the model of the environment, and then the agent plans using the model. The models need to be updated often.

Model-free: The environment’s model is not built. The agent is allowed to choose an optimal way to behave according to an optimal policy or its optimal value-function.

Figure 2 shows a reinforcement learning taxonomy that shows the interconnection of these classifications.

Figure 2 - Reinforcement Learning Taxonomy



Source: Odonkor and Lewis (2018)

2.3.1 Elements of Reinforcement Learning

2.3.1.1. States

The state S_t is defined in order to formulate the maintenance problem as a Markov Decision Process (MDP). All RL problems are needed to be modelled as an MDP (SUTTON, BARTO, 2018). For example, in a pump case, the state S_t assembles all the pump-level and system-level information that are essential to make maintenance decisions (HUANG, CHANG, ARINEZ, 2020). This is represented as a vector with multiple entries that contain all information relevant to the decision such as, but not limited to: performance features, pump inventory (max capacity, feeding, receiving), preventive maintenance task frequency for each pump, task duration etc.

For example, a system that is measured by its performance variables such as; vibration, V_t , temperature, T_t and pressure P_t would have a state matrix definition as:

$$S_t = \begin{matrix} V_1 & T_1 & P_1 \\ V_2 & T_2 & P_2 \\ V_t & T_t & P_t \end{matrix}$$

The kind of system state is determined by the type of conditions the equipment is being subjected to. For example, in a pump with deteriorating quality states, the state could be grouped into 0 for operating, 1 for deteriorating and 2 for failed state (WANG et al., 2014). So, the matrix is shown to the algorithm as a combination of discrete state variables.

2.3.1.2. Actions

The type of environment presented to an agent will determine the set of actions on which the agent will choose from (SUTTON, BARTO, 2018). Based on state S_t at time step t, an action A_t would be selected according to some rules and implemented in the environment. The actions in the context of preventive maintenance involves decisions to make according to the followed policy. For example, in a typical order dispatching industry, the related actions could be which order to process next, which machine shall the order be assigned to, chosen by learning agents (STRICKER et al., 2018).

The action a_t is a vector consisting of m binary variables indicating the type of maintenance action to be taken on the pump in Equation (2.1).

$$a_t = [a_1(t), a_2(t) \ldots\ldots a_m(t)] \tag{2.1}$$

Where $a_i(t)\ could\ be$: $\begin{cases} 0, & Leave\ pump\ as\ it\ is \\ 1, & perform\ maintenance \end{cases}$

Every time the state S_t is visited, the action a_t is selected among all available actions according to the ϵ-greedy policy π. the learning agent selects exploitative actions (i.e., actions with the largest value, maximizing the expected future rewards) with probability 1- ϵ, or exploratory actions, randomly sampled from the other feasible actions, with probability ϵ (ROCCHETTA et al., 2019). One thing to note in the operation of pumps is that the system spends most of the time in states of normal operation (FRANK, MANNOR, PRECUP, 2008), in order to reduce this possibility, it is suggested that the agent's exploration and interaction with the environment should be divided into episodes of fixed length (ROCCHETTA et al., 2019). In RL generally, PM actions are taken less frequently with a tendency to keep operating the equipment (ROCCHETTA et al., 2019).

2.3.1.3. Agent

The agent of an RL learns what action to take for each situation it encounters in order to maximize a cumulative reward, which responds to the agent's objective (BARDE, YACOUT, SHIN, 2019). Many real-world applications require several agents, which makes learning more difficult, each agent sees a non-stationary environment and also reacts to other agents, increase in the number of agents causes an increase in the curse of dimensionality (VAZQUEZ, NAGY, 2019). The interaction of the components of an equipment leads to a large state space which becomes intractable with traditional based planning PM methods (HUANG, CHANG, ARINEZ, 2020). When failures are independent among components of an equipment, a single agent is needed. A multi agent RL algorithm is deployed where failures of the components are dependent. Multi-agent systems can perform better than a single agent or multiple agents sharing single knowledge base (BARTO, CRITES, 1996). A manufacturing control system using RL architecture consists of 'resource agents' for the pumps, 'part agents' for the tanks containing oil and an 'observer agent' to control the process- this is a multi-agent case example (AISSANI, BELDJILALI, TRENTESAUX, 2009).

2.3.1.4. Reward Function

A reward function defines the goals in a RL problem. It maps perceived states or (state-action pair) of the environment to a single number, indicating the intrinsic desirability of the state (ABDULHAI, KATTAN, 2003). The reward signal or function of the agent is aligned to achieve the system's objectives (STRIKER et al., 2018). A typical example of a reward function as it relates to an air-conditioning system could be determined by the viability of thermal comfort which can be mathematically estimated from the occupants, failing to meet the set threshold would lead to a negative reward. Rewards are being set by rules, in Hajgato, Paal and Gyires-Toth (2020), the reward r is given to an agent if it gets closer to the reference solution on a monotonous trajectory. They made the reward function depend upon the state value and some other parameters of the environment. Reaching a terminal state involves allowing the agent to run until a fixed number of steps or the environment keeps track of the number of steps and this is terminated when an episode ends (HAJGATO, PAAL, GYIRES-TOTH, 2020). There is no restriction on the definition of a reward function but a well-suited reward function will help the agent converge faster to an optimal solution (SUTTON, BARTO, 2017).

In a simple MDP, no rewards are assigned to most intermediate states except to the goal state whereas in complex MDP, which is composed of multiple sub-modules, the reward function combines several reward sub-functions that evaluate the different sub-tasks.

The general framework for a reward function which reflects the goodness of the action a_t in state S_t is in Equation 2.2

$$G_t = r_t + \sum_{k=1}^{\infty} \gamma^k r_{t+k} \qquad (2.2)$$

Where, γ is a discount factor which is used to make a trade-off between immediate and future rewards.

The reward for maintenance problems is negative because we seek to maximize the accumulated reward and equivalently the overall maintenance cost can be minimized.

In discounting, immediate rewards contribute more to the sum, i.e. A dollar today is worth more than a dollar in a year’s time.

$\gamma = 0$, agent only cares about immediate reward

$\gamma = 1$, agent takes future rewards more strongly.

2.3.1.5. Markov Decision Process

The Markov property states that the future is independent on the past given the present. MDPs are a way that combines ML methods with dynamic programming, it sums up the basic framework of an RL learning process.

A Markov Decision Process is a tuple (S, A, P, R, γ)

S = finite set of states

A = finite set of actions

P = state probability matrix

R = reward function $R_s^a = \in [\, R_{t+1} \mid S_t = s, A_t = a]$

γ = discount factor, $\gamma \in (0,1)$

Maintenance modeling and Markov decision chains have a large joint history. For both areas the main research started in the fifties (DEKKER, NICOLAI, KALLENBERG, 2014). Maintenance problems have been among the first applications of Markov decision chains, as the model both allows a modeling of the deterioration as well as the determination of the structure of optimal policies (SASIENI, 1956).

MDP is particularly a common modelling method for maintenance problem in complex systems because maintenance is a sequential decision-making problem with multi-dimensional states and actions (HUANG, CHANG, ARINEZ, 2020).

2.3.1.6 Bellman Equations

The bellman equation is a central element of RL algorithms that is required to calculate the state-value or state-action function. According to this equation, long-term reward in a given action is equal to the reward from the current action combined with the expected reward from the future actions taken at the next step. Its idea is to find the optimal solution of a complex problem by breaking it down to simpler, recursive subproblems and finding their optimal solutions. There are 2 cases of using the Bellman equations.

a) Value Function

Value-function also known as the state-value function $V(s)$ measures how good it is to be in each state according to the return G when following a policy π.This is the expected total discounted reward that is obtainable from the state as given in Equation (2.3):

$$V_\pi(s) = E_\pi[G_t | S = S_t] = E_\pi[\sum_{j=0}^{T} \gamma^j r_{t+j+1} | S = S_t] \tag{2.3}$$

This describes the expected value of the total return G ,at time step t starting from state S at time t and then following policy π . The expectation $E[.]$ shows that the environment transition function might act in a stochastic way.

Hence the Bellman equation for the state-value function is given as Equation (2.4):

$$V_\pi(s) = \sum_a \pi(a \backslash s). \sum_{s'} P_{ss'}^a (r(s,a) + \gamma V_\pi(s')) \tag{2.4}$$

Where, $P_{ss'}^a$ means the probability of taking an action a , in state s and ending up in state s' with reward r from the previous state s.

The equation (2.4) shows how to compute the value of a state s following a policy π. It recursively breaks down the value computation into an immediate expected reward from the next state, $r(s,a)$, plus the value of the successor state $V_\pi(s')$, with the discount factor γ. This is also useful in a stochastic environment.

b. State-action function

The state-action function defines a value for the state-action pair, which is called the action-value function or the Q-function. It defines the value of taking action a in state s under a policy π, denoted by $Q_\pi(s,a)$, as the expected return G starting from s, taking the action a, and thereafter following policy π.

This is written as in Equation (2.5):

$$Q_\pi(s,a) = E_\pi[G_t|S_t = S,\ A_t = a] = E_\pi[\sum_{j=0}^{T} \gamma^j r_{t+j+1}|S_t = S|A_t = a\ ] \quad (2.5)$$

The Bellman equation for the action-value function is as Equation (2.6):

$$Q_\pi(s,a) = \sum_{s'} P_{ss'}^{a}(r(s,a) + \gamma \sum_{a'} \pi(a' \backslash s').\ Q_\pi(s',a')) \quad (2.6)$$

The equation 6 shows how to find recursively the value of the state-action pair following a policy π.

It is shown in Sutton and Barto (2012) that the state-value function $V(s')$ is equivalent to the sum of the action-value functions $Q(s',a')$ of all outgoing actions a' multiplied by the policy probability of selecting each action, $\pi(a' \backslash s')$ .This is exhibited in Equation (2.7):

$$V_\pi(s') = \sum_a \pi(a' \backslash s').\ Q_\pi(s',a') \quad (2.7)$$

Substituting equation 7 in the right-hand side of the Bellman equation 2.6, we have, Equation (2.8):

$$Q_\pi(s,a) = \sum_{s'} P_{ss'}^{a}(r(s,a) + \gamma V_\pi(s')) \quad (2.8)$$

c. Optimal Policy

The optimal policy is the policy that maximizes the total cumulative reward. This is the goal of an RL agent. The optimal value function is the one which yields maximum value compared to all other value function following using other policies.

The optimal state-value function is mathematically expressed as Equation (2.9):

$$V_*(s) = \max_\pi V_\pi(s) \quad (2.9)$$

With the same analogy, the optimal state-action value function indicates the maximum reward one can get if in state s and taking action a from there onwards. See Equation (2.10):

$$Q_*(s,a) = \max_\pi Q_\pi(s,a) \quad (2.10)$$

It is possible to define $V(s)$ through $Q(s,a)$ so that the value of some state equals the value of the maximum action one can execute from this state, i.e.,

$$V(s) = \max_a Q(s,a) \tag{2.11}$$

And, $V_*(s) = \max_a Q_*(s,a)$ (2.12)

Armed with this knowledge of optimality, equations 2.4 and 2.6 can be re-written as Bellman equations of optimality for the state-value function and state-action function as shown in Equations (2.13) and (2.14) respectively.

$$V_*(s) = \max_a \sum_{s'} P_{ss'}^{a}(r(s,a) + \gamma V_*(s')) \tag{2.13}$$

Equation 2.13 proves that the optimal state-value function in a state s is equal to the action a, which gives the maximum possible expected immediate reward, plus the discounted long-term rewards for the next state s'.

$$Q_*(s,a) = \sum_{s'} P_{ss'}^{a}(r(s,a) + \gamma \max_a Q_*(s',a')) \tag{2.14}$$

Equation 2.14 proves that the optimal state-action value function for selecting an action a in state s gives the reward in the previous state plus the discounted maximum Q-function of selecting action in the succeeding state-action pairs.

The solutions to the above equations (2.13 and 2.14) are the motivation for solving the RL MDP problem.

2.3.1.7 Exploration and Exploitation

In an RL environment, the decision for the agent to exploit an action a in state s enables making the best decision given the current information. However, by always making that same decision in the current state may lead to neglecting other rewards possible in unexplored states. Exploration is the process of gathering more information from other states. A very specific challenge for RL is the trade off between these two processes (exploration and exploitation) (WUEST et al., 2016).

In other to solve the above challenge, several methods have been proposed, amongst them are random exploration and information state space.

Random exploration is a situation where the agent explores random actions. Notable is the greedy method.

Information state space is where one considers the agent's information as part of the state and look-ahead to see how information helps in maximizing reward. This is the most theoretically correct method but it is not being explored in literature due to its computational expense.

In terms of the greedy method, there are 3 techniques:

a. Strictly greedy: the strictly greedy algorithm selects actions with the highest value, i.e., $A_t = \underset{a \in A}{\operatorname{argmax}} Q_t(a)$. It has the disadvantage of locking itself to suboptimal action forever. It also has a linear total regret.

b. Epsilon greedy ($\varepsilon - greedy$): The epsilon greedy method selects actions according to the following probabilities:

$$\begin{cases} A_t = \underset{a \in A}{\operatorname{argmax}} Q_t(a) & 1 - \varepsilon \\ \quad random\ action & \varepsilon \end{cases}$$

The ε -greedy explores too much because even when one action seems to be optimal, the method keeps allocating a fixed percentage of the time for exploration. Thus, missing opportunities and increasing total regret.

c. Decaying ε -greedy: for the decaying ε -greedy, it picks a decay schedule for $\varepsilon_1, \varepsilon_2, \varepsilon_3 \ldots . \varepsilon_n$.

This method has logarithmic asymptotic total regret which gives a much better result than the two aforementioned. The major challenge is being able to perform the right decaying processes by choosing the right parameters.

2.4 REINFORCEMENT LEARNING APPLICATIONS ON PUMPS

In the literature, there are several strategies based on artificial intelligence methods for improving pump's availability. For instance, the availability of a pump can be improved by forecasting the remaining useful life (RUL) using machine learning techniques (TSE, CHOLETTE, TSE, 2019; GUO et al., 2020). When pump maintenance procedures are optimized, they lead to lower maintenance cost which can also increase the availability of pumps (KIMERA, NANGOLO, 2020;

ADAZEH et al., 2013). One of the objectives of the reinforcement learning work done in this thesis is aimed at lowering maintenance cost.

However, most of the reinforcement learning applications on pumps in the literature are centered on developing a control system Urieli and Stone (2013) and Ruelens et al. (2015), lowering energy consumption Vázquez-Canteli, Kämpf and Nagy (2017), Candelieri, Perego, and Archetti (2019), YongXiu et al. (2021), Jiahui et al (2021) and Huang et al. (2021), developing optimal operational schedules Correa-Jullian, López Droguett, and Cardemil (2020) and Donâncio, Vercouter, and Roclawski, (2022), and improving demand response (VAZQUEZ, NAGY, 2019; PATYN, RUELENS, DECONINCK, 2018). In the aforementioned works, the heat pumps or Heat, Ventilation and Air conditioning (HVAC) systems. To the best of the author's knowledge, none was based on centrifugal pumps.

2.4.1 **Reinforcement Learning Algorithms on Pumps**

The RL algorithms applied to pumps as reviewed in the literature (years 2013-2022) are shown in Table 1

Table 1 - RL algorithms applied to Pumps

Reinforcement learning method	References
Q-learning	(OROOJENI et al., 2015; YANG et al., 2015; ZHU, ELBEL, 2018; QIU et al., 2020; ABE, OH-HARA, UKITA, 2022; WU et al. 2022)
Proximal Policy Optimization (PPO)	(FILIPE et al., 2019; SHAO et al., 2020; JIAHUI et al., 2021; GHANE et al., 2021; SEO et al., 2021; DING et al., 2022)
Fitted Q-iteration (FQI)	(RUELENS et al., 2015; RUELENS et al., 2017; VÁZQUEZ-CANTELI, KÄMPF, NAGY, 2017; PEIRELINCK, RUELENS,

	DECNONINCK, 2018; MBUWIR et al., 2020; SOARES et al., 2020).
Deep Deterministic Policy Gradient (DDPG)	(LIU et al. 2019; CHRISTENSEN, ERNEWEIN, PINSON, 2020; SALIBA et al., 2020; WANG et al., 2020; LI, YU, 2021a; LI, YU ,2021b)
Deep Q-networks (DQN)	(WU et al., 2018; WANG, XUAN, 2021; MULLAPUDI et al., 2020; AHN, PARK, 2020; SEO et al., 2021; FU et al., 2022; DANIEL, MARTIN, 2022; CHO, PARK, 2022)
Double Deep Q-Networks	(HUANG et al., 2021; AMIRREZA, FRANCOIS, DOLAANA, 2021).
Soft Actor-critic (SAC)	(VAZQUEZ-CANTELI, HENZE, NAGY, 2020; PINTO, DELTETTO, CAPOZZOLI, 2021; ANDERSON, STEWARD, 2021)
Integral reinforcement learning (IRL)	(JINGREN, QINGFENG, TAP, 2019)
Dueling Deep Q-networks	(HAJGATÓ, PAÁL, GYIRES-TÓTH, 2020)
Parallel learning	(FU et al., 2022)
Transfer learning	(PAULO et al., 2021)
Behavioral cloning	(LEE, ZHANG, 2021)

Source: This Research (2023)

As seen in table 1, the Deep Q-Networks (DQNs) have been most explored as RL application to pumps. It is more powerful than the Q-learning because it uses a neural network to perform q-value function approximation (SUTTON, BARTO, 2012). Because of this reason, the author of this thesis used the DQN in his work described in chapter 3.

2.5 DEGRADATION PROCESSES

An effective maintenance policy requires an appropriate model that can replicate the degradation of a system and thereby provide a better maintenance prediction (MITRA et al., 2022). It is therefore necessary to study the degradation process of such system. The author limits the literature review to degradation processes of centrifugal pumps.

Several models have been deployed to model a pump's degradation in literature. Such models include, the gamma process Duan, Li and Liu (2020) and Omar et al. (2018), the wiener process Omar et al. (2018) and the variance gamma (VG) process (SALEM, FOULADIRAD, DELOUX, 2021a; MITRA et al., 2022). These models are all stochastic because they are capable of integrating the temporal uncertainty associated to the evolution of degradation. The above listed models will be discussed in this review.

2.5.1 The Gamma Process

Gamma process is a stochastic process with an independent non-negative gamma distribution increment with identical scale parameter monotonically increasing over time in one direction which is suitable to model gradual damage such as wear, fatigue, corrosion and erosion (ZHANG, TEEA, 2019).

It is defined as a time-independent stochastic process, $\{X(t), t \geq 0\}$ where, $X(t)$ is a random quantity for all $t \geq 0$.

According to Edirisinghe, Setunge, and Zhang, (2013), the gamma process consists of these three main conditions ? :

a. $X(t) = 0$ with probability of 1
b. $X(t)$ has independent increments
c. $X(t) - X(s) \sim Ga(V(t-s), u)$ for all $t > s \geq 0$.

The probability distribution function in Equation (2.15)

$$Ga(X\backslash V,u) = \frac{u^V}{\Gamma(V)} X^{V-1} e^{-uX} I_{(0,\infty)}(x) \tag{2.15}$$

Where, V is the shape parameter, u is the scale parameter, and $I_{(0,\infty)}(x) = 1$ for $X \in (0,\infty)$.

$$I_{(0,\infty)}(x) = \begin{cases} 1 & x \in (0,\infty) \\ 0 & x \notin (0,\infty) \end{cases}$$

The complete gamma function for $\Gamma(V)$ for $V \geq 0$ is defined as in Equation (2.16)

$$\Gamma(V) = \int_0^\infty X^{V-1} e^{-x} dx \tag{2.16}$$

Some studies that have considered the gamma process for modelling the degradation process in pumps include; Wang, Scarf and Smith (2000) who modelled the failure rate of water pumps at a large soft drinks manufacturing plant by a non-stationary gamma process. In Nabila et al. (2019), it was determined that the degradation path of a motor pump follows a gamma process model with covariates. Therefore, they introduced a covariate parameter in the degradation model of the pump in order to predict maintenance action and improve the Remaining Useful Life (RUL) of the motor pump. In Duan, Li and Liu (2020), a CBM policy with stochastic maintenance quality was proposed for ship pumps by characterizing the degradation of the pumps using a non-homogeneous gamma process.

The gamma process is a good candidate to model a monotonic trend degradation in the presence of tractable mathematical computation (SALEM, FOULADIRAD, DELOUX, 2021a; MITRA et al., 2022). However, degradation of a centrifugal pump is complex and follows a non-monotonic behaviour. Hence, researchers sought better methods to model the degradation of these complex behaviours.

2.5.2 The Wiener Process

The wiener process is a real-valued continuous-time stochastic process. It is a constant random process keeping the variance per time a constant. It is also referred to as a Brownian process.

For a wiener process, suppose $\{X(t)/\ t \geq 0\}$ is a Wiener stochastic degradation process, which is expressed in Equation (2.17)

$$X(t) = X_0 + \mu t + \sigma B(t) \tag{2.17}$$

Where, X_0 is the initial degradation, μ and σ represent the drift and diffusion coefficient respectively. $B(t)$ is the standard Brownian motion, which is used to describe the uncertainty of degradation on the time axis (WANG, MA, ZHAO, 2019).

The degradation increments $\Delta X(t)$ of the wiener process are independent and identically distributed, following a normal distribution, written as Equation (2.18) (LI et al., 2022).

$$\Delta X(t) = X(t + \Delta t) - X(t) \sim N(\mu\Delta t,\, \sigma^2 \Delta t) \tag{2.18}$$

The probability distribution function of $\Delta X(t)$ is shown in Equation (2.19) and its density function $f(\Delta x) = f(u)$ of $\Delta X(t)$ is shown in Equation (2.20)

$$P\{\Delta X(t) < x\} = P(\mu < x) = \frac{1}{\sqrt{2\pi\sigma^2\Delta t}} \int_{-\infty}^{x} \exp\left(-\frac{(\mu - \mu\Delta t)^2}{2\sigma^2\Delta t}\right) du \tag{2.19}$$

$$f(u) = \frac{1}{\sqrt{2\pi\sigma^2\Delta t}} \exp\left(-\frac{(\mu - \mu\Delta t)^2}{2\sigma^2\Delta t}\right) \tag{2.20}$$

Some works on application of the wiener process are found in Li et al., (2019) where a random effect wiener process was developed to model the de-noised degradation data of airborne fuel pump in order to predict its RUL. Omar et al. (2018) modelled a non-monotonic feature of the degradation process for a motor pump using the wiener process. An aviation hydraulic axial pump degradation process was modelled using the wiener process in order to predict its RUL (WANG et al., 2016). The wiener process is noted to account for random and uncertain characteristics of the wear process.

Though a wiener process can model a non-monotonic degradation process, the degradation path of a centrifugal pump consists of high frequency deterioration followed by phase of where the deterioration intensity is comparably low which results in a skewed or large tail increment deterioration distribution that a wiener process cannot handle. Another disadvantage of using a wiener process is that its randomness moves in a too uniform way over time (RALF, ELKE, GERALD, 2010). Because of the above reasons, the variance gamma process becomes a preferable option to model the deterioration of a centrifugal pump additionally by the fact that it is non-monotonic, it accounts for a skewed behaviour and its increments are independent (MITRA et al., 2022). This is discussed next.

2.5.3 The variance gamma process

The Variance Gamma (VG) is a stochastic process, also known as a Laplace motion determined by a random time change. The characteristic features include:

a. It has finite moments that distinguishes it from many levy processes.
b. It is a pure jump process

c. The increments are independent and they follow a VG distribution.

For history of the evolution of the variance gamma process, please refer to Seneta and Madan (1990).

A VG process can be defined a Levy process (continuous-time analogue of a random walk) which can be written as a Brownian motion $w(t)$ with drift θt subjected to a random time change that follows a gamma process $\Gamma(t;\ \mu, v)$ in Equation (2.21)

This is written as $X^{VG}(t;\ \sigma, v, \theta) \coloneqq\ \theta\Gamma(t;\ \mu, v) +\ \sigma w\Gamma(t;\ \mu, v)$ (2.21)

Where, σ defines the volatility and θ defines the drift.

μ and v are defined as the mean and variance of the gamma process with μ^2/v as the shape parameter and $\mu/\ v$ as the scale parameter with $\mu > 0$ and $v > 0$.

As can be seen from Equation 2.21, there are four parameters involved in the transition probability. The volatility of the time changes process and the drift parameter permit the control of the Kurtosis and skewness (MITRA et al., 2022).

The characteristic function of the VG is given by Equation (2.22)

$\phi_X(u;t) = \left(\frac{1}{1-i\theta uv+(\sigma^2 v/2)u^2}\right)^{t/v}$ (2.22)

The VG can be represented in several ways (RALF, ELKE, GERALD, 2010). Two of such ways are by subordination and by differences of two gamma processes. The presentation of the later proves an advantage of a VG being used as a degradation model of a centrifugal pump because the first part of the model presents the increase in degradation and the second part presents the decreases (MITRA et al., 2022).

Some popular works on centrifugal pump using the VG process includes works by Salem, Fouladirad, Deloux, (2021a) where the non-monotonic degradation of a centrifugal pump system in the dynamic environment was considered and modelled using the VG stochastic process. Salem, Fouladirad, Deloux, (2021b) by the same authors modelled the degradation of a water tank centrifugal pump using the VG process. Mitra et al. (2022) used the VG process to model the degradation of a centrifugal pump by considering the real data of its rate of leakage.

2.6 FINAL REMARKS ON THE CHAPTER

This chapter provides a comprehensive overview of various maintenance policies and the existing literature on this subject. The delay-time model is well explained, and different authors who have contributed to this area are cited. The chapter discusses the major challenge of designing appropriate models that optimize inspection intervals, and it establishes the link between the delay-time and inspection policy.

Opportunistic maintenance is also explained in detail, with evidence from the literature showing that it is better suited for a multi-component environment than age-based or block replacement policies. However, the challenge of finding the best combination of corrective maintenance (CM) and preventive maintenance (PM) activities that optimize the total opportunistic maintenance (OM) cost is presented as a research opportunity. The importance of deploying an OM policy in a standby system is also discussed using relevant literature.

The chapter also explores machine learning algorithms, particularly the branch of reinforcement learning, and how this field can be adopted to improve equipment maintenance, using a pump as a case study.

Finally, various degradation processes used to model equipment failure processes in the literature are discussed. Special attention is given to the variance gamma degradation process model, which is currently considered the best option for modeling a pump's degradation process due to the non-monotonic nature of its behavior.

3 APPLICATION OF REINFORCEMENT LEARNING FOR OPTIMAL CONDITION BASED MAINTENANCE POLICY IN A CENTRIFUGAL PUMP

In this chapter, a condition-based maintenance reinforcement learning approach was proposed for centrifugal pumps used in the production of iron ore concentrates. These pumps play a crucial role in the transportation of slurries from one point of production to another but they are prone to incessant stoppages that halt the production process. The proposed framework recommends actions to be taken based on its temperature, pressure, and vibration performance features. A variance gamma process degradation model was developed to simulate the degradation process of the pump. The recommended actions aim to minimize maintenance costs over the long-term. The model was compared to a corrective maintenance policy and results indicated that it significantly outperformed the corrective policy in terms of average maintenance costs. A sensitivity analysis was carried out to assess the resilience of the trained reinforcement learning agent. The analysis demonstrated the agent's effectiveness by revealing that a pump with slower degradation would result in lower maintenance costs and fewer stoppages during a designated period. The results of this study demonstrate the potential of the proposed approach for improving maintenance strategies of centrifugal pumps used in the iron ore industry.

Following is a detailed description of the study area and the process unit of an iron ore mining company in Nigeria that lays the foundation for the works in this chapter and chapter 4.

3.1 STUDY AREA OF NATIONAL IRON ORE MINING COMPANY

The study area is an Iron ore producing industry located in Nigeria. The major focus of the research in this industry is at the beneficiation plant. Beneficiation is the process of improving the quality of an iron ore deposit from a lower grade (typically less than 36 per cent iron) to the 63-68 per cent iron concentration required by steel companies.

The Beneficiation line comprises of Reclaimer, Repartition bins, grinding mills wet screening plant, Beneficiation plant and its annex building, thickener, concentrate storage and loading station. The focus is in the beneficiation plant, and specifically in the filtration unit (see Figure 3). Centrifugal pumps are one of the world's most commonly used devices in a process plant (SAM, 1996). Apart from this, they also account for about 20% of the world’s total energy consumption (ARUN SHANKAR et al., 2016). Ultimately, in the plant we studied, these pumps make up about

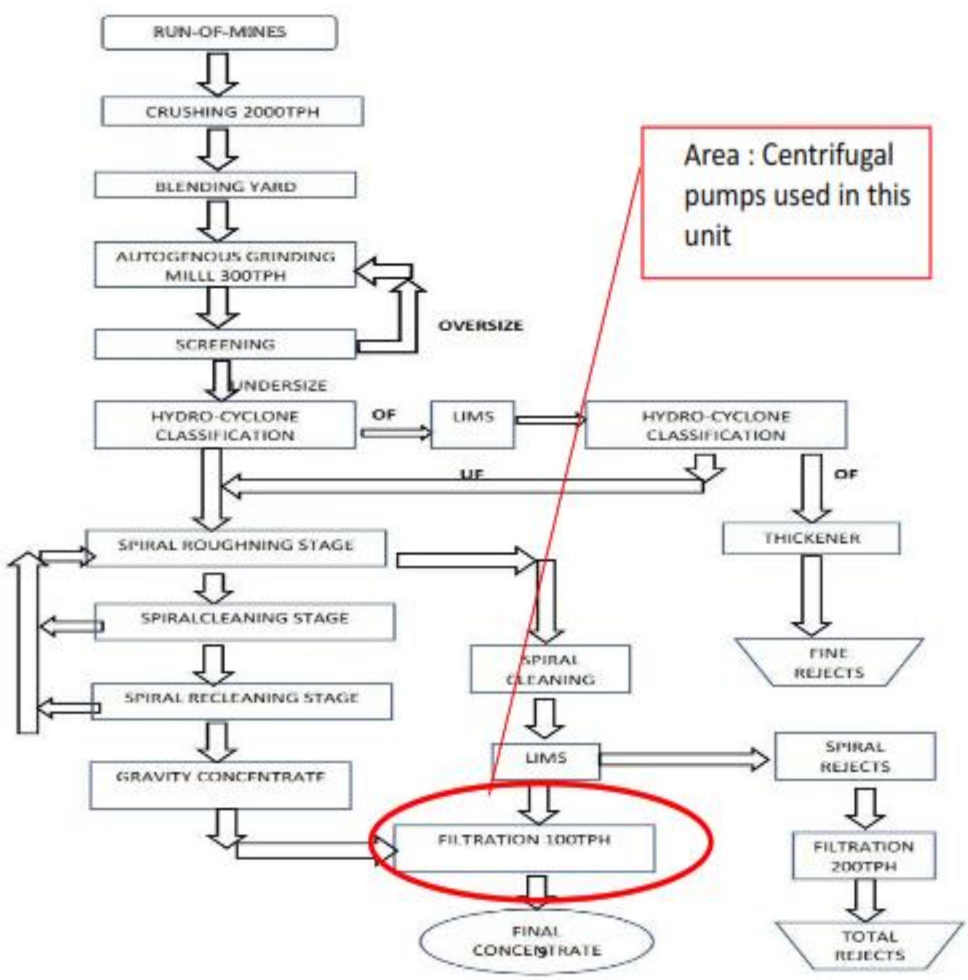
40% of the total equipment involved in the production process. The degradation of these pumps is linked to the productivity of the beneficiation line. If they are well maintained, they guarantee a continuous flow of ore in the line. A centrifugal pump is a mechanical device that is mainly used in industrial applications to increase the energy content of a fluid flowing through it (GEVORKOV et al., 2018). The impeller converts the energy of the prime mover into the pressure energy of the working fluid. The brief description of the process of iron ore production is explained in section 3.2.

3.2 BRIEF DESCRIPTION OF IRON ORE BENEFICIATION PROCESS DESCRIBING THE ROLE OF PUMPS

Several components make up the beneficiation plant (Figure 3). Iron ore from run-off mines is delivered to a crushing machine with gigantic crushers with a capacity of 2000 tons per hour (TPH). The ore is crushed to sizes from 1m to about 1mm to 200mm. The crushed ore is transported to a blending yard, where it is reclaimed using a wheel reclaimer situated on a bridge. Convey belts transfer the ore to a 2,500-ton repartition bin (not depicted in the Figure). The repartition bin is divided into three divisions, each of which links to one of three identical production lines that can be used at any moment. The ore is extracted from the bin (through one of the production lines) and fed into a 300 TPH Autogenous Grinding Mill- one for each production line (shown in Figure 4). Water is introduced at the AGM, and the slurry is handled by centrifugal pumps.

The AGM grinds the ore from the particle size of 0- 6mm to sizes of 0-1.6mm, (called undersize). This undersize is sent to the screening unit by centrifugal pumps. Some ore escapes the required grinding size (0-1.6mm) from the AGM and is pumped back to the AGM for refined grinding. The slurry from the screens is pumped into the hydro-cyclone classification unit. The hydro-cyclone produces two separate slurries: overflow (OF), which is silica-rich trash, and underflow (UF), which is a substance high in iron ore concentrate. The overflow is directed to the Low-Intensity Magnetic Separator (LIMS), where the magnetite is recovered and processed through another hydro-cyclone before being delivered to the spiral feed. The thickening unit receives the unrecovered flow and processes the tailings (also known as rejects). Stationed centrifugal pumps carry the underflow into the spiral unit. The material is subjected to a gravity separation procedure during the spiral (roughening, cleaning, and recleaning) phases, which is used to extract more iron ore concentrates. The material is delivered into the top feed of the spirals using heavy-duty centrifugal pumps. The material, which is now iron ore concentrate rich, is filtered and sent to a storage yard for sale. Spiral rejects are also processed through another set of LIMSs for the possible recovery of iron ore-rich products, unrecovered or final rejects from this stage are transported to the tailings storage yard. The centrifugal pumps being used in NIOMCO are mainly of the Warman model (WARMAN PUMPS, 1999). The unit of concentration in this work is highlighted in red in Figure 3. As can be observed from the description, centrifugal pumps are of immense importance in this industry.

Figure 3 - Beneficiation Plant Flow Chart



Source: adapted from Chinedu and Nwaeto (2018)

Figure 4 - Autogenous Grinding Mills

Source: The author, 2023

3.3 THE PROBLEM STATEMENT

The company currently practices corrective maintenance on the centrifugal pumps when they are degraded. Studies have shown that the practice of corrective maintenance leads to higher cost and decrease in a system's reliability (MARTINUS et al., 2019). On the issue of maintenance costs, Hydraulic Institute (2001) proved that maintenance costs contribute about 30 – 45% of the total life cycle of industrial pumps, therefore, research has been ongoing in seeking optimal ways of reducing these costs to the bearable minimum. In order to reduce these costs, one of such suggested ways is to reduce maintenance activities (MARTINUS et al., 2019). The industry performs this reduction of maintenance activities by installing auxiliary centrifugal pumps which are switched on only when the primary pump fails, the demerit of this is that in the long run, it becomes a costly solution since the failed pump's life could have been extended and repairs could have been less costly if they were caught prior to failure. It can therefore be said that corrective practice on the pumps is not efficient to guarantee a continuous flow of production.

In order to solve this problem and strike a balance between reducing maintenance cost and maintenance activities, a good solution is a condition-based maintenance (CBM). It is a predictive maintenance technique. Predictive maintenance is based on the inspection and condition monitoring of machine conditions, operating frequency, and other indicators of in-service equipment on a regular basis (OPREA, POPA, ONESCU, 2014). According to CBM, maintenance should only be done when specific indicators indicate that performance is deteriorating or that breakdown is imminent. Non-invasive measures, visual examination, performance indicators, and planned testing can all be used to check a machine for these indicators. Data on the condition can then be collected at predetermined intervals or continuously (as is done when a machine has internal sensors). CBM/predictive maintenance are fast becoming the preferred maintenance technique because of the advent of faster processing CPUs, remote sensors, database software, computerized maintenance procedures which utilize expert as well as algorithmic decisions (JAY et al., 2014).

The pump undergoes degradation as a result of usage, and this degradation can be monitored by observing various variables, such as temperature, pressure, and vibration. These variables provide insights into the condition of the system, but a conclusive assessment can only be achieved through inspections. Consequently, the maintenance of the system is contingent upon its condition, which is evaluated during periods of stoppage. Understanding the failure process of the pump proves challenging due to uncertainties arising from operational conditions, demand fluctuations, and environmental factors (CANDELIERI, PEREGO, ARCHETTI, 2018; TANAKA, TSUKAMOTO, 2018). Although certain machine learning (ML) techniques may perform well in scenarios devoid of these uncertainties, addressing this challenge necessitates the adoption of a more adaptable and flexible approach. Reinforcement Learning (RL) has demonstrated its efficacy as a valuable machine learning technique in the realm of maintenance decision-making and optimization. RL possesses the capability to strike a balance between short- and long-term implications, namely the immediate effects of maintenance actions as opposed to the overall benefits in terms of maintenance and operational costs. This characteristic renders RL particularly suitable for application within the maintenance domain (HAMED et al., 2021). Moreover, the iterative nature of the agent's learning process, characterized by trial-and-error and direct interaction with the environment, bestows the RL approach with enhanced adaptability and flexibility in accommodating process modifications (MEINDL, LEHMANN, SEEL, 2022). Therefore, the present study employs reinforcement learning (RL) technique. RL has demonstrated effectiveness in maintenance optimization and decision-making (SIRASKAR et al., 2023; HAMED et al., 2021). It is a model-free strategy that does not require probability transition matrices of the system to converge towards an optimal maintenance policy (DOODY, VAN SWIETEN, MANOHAR, 2022;

SINAN, MELTEM, 2019). By observing the system's variables, the RL agent acquires knowledge about its failure behavior and dynamically recommends the most opportune time for stoppages.

3.4 MAJOR CONTRIBUTION(S)

The recent studies, Mitra et al., (2022), Salem, Fouladirad, Deloux, (2021a) and Salem, Fouladirad, Deloux, (2021b) considered the leakage rate due to a centrifugal pump seal failure as the degradation data. Although they all modeled this degradation using the variance gamma process, this work is different from these because health indicators such as pressure, temperature and vibration as performance data of the pump are considered. These indicators are used for the degradation model which is based on the variance gamma process. The justification of using these performance indicators is explained in section 3.7.1.

Another contribution of this study is to develop a reinforcement learning agent on a centrifugal pump used in an iron ore process plant. The RL agent learns the best action (do nothing or stop the pump) to take at each time step. This involves the online continuous monitoring of the performance of the pump. At each time step, the operator can be notified about the best time to stop the pump for maintenance activities. These actions are performed at an optimal reduced maintenance cost developed as the reward function.

3.5 METHODOLOGY

To propose an optimal condition-based maintenance policy for centrifugal pump used in the company of study, the application of reinforcement learning (RL) specifically a Deep Q- Network (DQN) technique was explored. The basic reason of using a RL to solve this problem is so as to cater for the uncertainties inherent in the environment of the working pump. These uncertainties are related to varying operating conditions such as; temperature, pressure and vibration. The RL technique has found applications in literature to pumps (URIEL, STONE, 2013; HAJGATO, PAAL, GYIRES-TOTH, 2020; SOARES et al., 2020). In many of the papers, an RL agent is developed in order to maintain, reduce energy consumption and optimize their performances. Introduction to the technique of RL with its area of application can be found at Sutton and Barto (2018). Centrifugal pumps, even though usually have an estimated service life of about 20 years, will degrade over time (HASHIM, HASSAN, HAMID, 2020). It becomes necessary to study the degradation pattern of the pumps in the company, model and simulate it to be presented as the states of the RL algorithm. This degradation is based on the performance indicators or features that determine the condition of the pump at each time step. The reinforcement learning (RL) agent receives input derived from degradation data, as illustrated in Table 5, consisting of continuous variables. In order to enhance the agent's learning process, the continuous variables associated with pump degradation have been organized into distinct categories (refer to Table 6). These discretized categories establish ranges that indicate whether the pump is in a state of good condition, degradation, or failure. The discretized ranges are determined based on the industrially acceptable operational range or predefined thresholds for each performance feature, as outlined in the Weir Group report of 2022 (THE WEIR GROUP, 2022). The primary objective for the RL agent is to acquire knowledge of these thresholds to optimize maintenance and make informed decisions regarding the pump's operation, deciding whether to stop or continue running at each iteration step of the algorithm.

3.6 DESCRIPTION OF THE PUMP

The type of pump in the industry is the Warman centrifugal horizontal slurry pump (THE WEIR GROUP, 2022). The function involves the transport of material known as slurry to different units for production process of iron ore concentrate. The slurry pumps (Warman 8/6AH) are of different sizes. They are used to feed material to the primary and secondary cyclone, the roughening and cleaning spirals of the beneficiation plant. The selected pump's specification for this study is shown in Table 2 and Table 3 shows the notations used in this work.

Table 2 - Pump description parameters

Pump function	Primary cyclone feed
Impeller diameter	510mm
Motor power rating	110KW
Type	8/6 AH
Materials	High chrome iron, natural rubber, polyurethane, corrosion resistant alloys
Size range/ dimensions	Discharge size 25mm to 450mm

Source: Warman Pumps (1999)

Table 3 - Notations and definitions

Notation	Definition
t	Simulation time
θ	Drift parameter of a Brownian motion
σ	Volatility parameter of a Brownian motion
μ	Mean parameter of the gamma process
v	Variance parameter of the gamma process
$\phi_X(u;t)$	Characteristic function of the variance gamma process
μ_p	Mean parameter of the gamma process representing the positive component
v_p	variance parameter of the gamma process representing the positive component
μ_n	Mean parameter of the gamma process representing the negative component
v_n	variance parameter of the gamma process representing the negative component
$\alpha^+(t)$	Positive component of the gamma process which is distributed as $\Gamma(t;\ \mu_p, v_p)$
$\alpha^-(t)$	Negative component of the gamma process which is distributed as $\Gamma(t;\ \mu_n, v_n)$
$X(t)$	The variance gamma distribution given as the difference of the gamma representations $\gamma^+(t) - \gamma^-(t)$
$SP_{t_i}, ST_{t_i}, SV_{t_i}$	Pressure, temperature, and vibration levels of the pump at time t_i
$a_n t$	Maintenance action at time t
R_t	Reward quantity at time t
C_e	Energy cost
C_r	Repair cost
C_m	Maintenance cost
C_p	Penalty cost.

C_f	Failure cost

Source: The author (2023)

3.7 MODELLING THE DEGRADATION PROCESS OF THE CENTRIFUGAL PUMP

As explained in chapter 2, section 2.5.3, the gamma and wiener process are good candidates to model the degradation of centrifugal pumps. However, the gamma process is only used when the system degradation shows a monotonic trend and its mathematical computations are tractable (ABDEL-HAMEED, 2010; LING, NG, TSUI, 2019). The Wiener process may not fit in degradation paths with skewed or large tail increment distribution (GUO et al., 2018). Therefore, the degradation process of the centrifugal pump in this work was modelled using the variance gamma (VG) process. The VG is represented as a case of the difference of two gamma processes. The two independent gamma processes are defined as $\alpha^{+}(t)$:= $\Gamma(t;\ \mu_p,\ v_p)$ and $\alpha^{-}(t)$:= $\Gamma(t;\ \mu_n,$ $v_n)$ with $\mu_p = \eta_p/v,\ \ \mu_n = \eta_n/v,\ \ v_p = {\mu_p}^2 v,\ v_n = {\mu_n}^2 v,$

With reference to the characteristic function of a VG (Equation 2.22), it can be split as Equation (3.1):

$$\phi_{\gamma+}(u;t).\ \phi_{\gamma-}(u;t) = \left(\frac{1}{1-i\eta_p u}\right)^{t/v}\left(\frac{1}{1+i\eta_n u}\right)^{t/v} \quad (3.1)$$

Where we have, η_p- η_n= $\theta v, \eta_p \eta_n = \frac{1}{2}\sigma^2 v$.

And the link between the parameters of the VG process and those of the difference between the gamma process parameters are represented by:

$$\eta_p = \frac{\theta v}{2} + \sqrt{\frac{\theta^2 v^2}{4} + \frac{\sigma^2 v}{2}} \qquad \eta_n = -\frac{\theta v}{2} + \sqrt{\frac{\theta^2 v^2}{4} + \frac{\sigma^2 v}{2}}$$

Therefore, the difference of gamma representation becomes:

$X(t)$= $\alpha^{+}(t)$ - $\gamma^{-}(t)$

Where, $\alpha^{+}(t) \sim \Gamma(t/v,\ \mu_p v)$, $\alpha^{-}(t) \sim \Gamma(t/v,\ \mu_n v)$,

3.7.1 Features for the deterioration model

It is possible to sense the operational status of a centrifugal pump, examine and evaluate its health status, by measuring physical quantities such as vibration and temperature (CHEN et al., 2022). Unnecessary increases in temperature and vibration accelerate degradation. The gland seal is the most significant function in the slurry pump that requires to separate the slurry from the external environment when the process pressure and temperature are high in the industry under investigation. This demonstrates that when temperature and pressure rise above a particular point, the gland seal can collapse (RIDGWAY et al., 2009). The most crucial condition for establishing gland life, according to Weir (2009), is the availability of gland flush water at the proper pressure. in the work of Mele, Guzzomi and Pan (2014), they investigated the correlation between pump vibration and unsteady flow at different pump speeds. Flow-induced vibration increases with pump speed which is invariably linked to pump efficiency; therefore, pump's performance can be deduced from its pressure and vibration levels, more energy is fed into the system and a greater amount of pressure can induce vibration responses. Excessive vibrations, are classified, according to ISO 10816, to have amplitudes larger than 2.80mm/s for small machines, 4.5mm/s for medium machines, 7.10mm/s for large machines with rigid foundations and 11.2mm/s for large machines with soft foundations (MCKEE et al., 2011). Vibration results from unbalanced moving parts found within the pump system, interactions of the fluid and its particles with the pump and the connecting pipes, and movements of the pipelines themselves. Beebe (2004) has published a list of vibration frequencies that can be found in a centrifugal pump, and the possible causes of each vibration. In addition, he published a table that contains the stages of bearing degradation and the vibration associated with each stage.

As a result of these, the author chose to study the pressure, temperature, and vibration performance data in order to model the pump's deterioration. The state of the reinforcement learning algorithm is determined by the combination of these factors.

The variance gamma process has four parameters, (θ, v, μ, σ). It is a flexible stochastic model that is capable of fitting to different time series with independent increments and non-monotonic paths. The parameters of the model are adapted to the work of Mitra et al. (2022) that also deals with the maintenance of centrifugal pumps (see Table 4). The degradation data was simulated by developing a Monte Carlo simulation in python so as to generate large data using the model's estimated parameters as shown in the pseudocode in section 3.7.1.1.

Table 4: Degradation model parameters

Performance feature	**Theta θ**	**v**	μ	σ
Temperature	0.077	0.5	0.5	0.01
Pressure	1.8	0.5	0.5	1.5
Vibration	0.0033	0.5	0.5	0.01

Source: The author (2023)

According to Mitra et al. (2022), the v and μ parameters do not have substantial impact on the degradation path trend, so they are kept constant at a value of 0.5 for all the three parameters. Instead, the values of θ and σ are noticed to affect the degradation path substantially.

Figures 5-7 shows the degradation path generated for each of the performance features. The red line indicates the start of degradation point. A snapshot of the degradation data generated is shown in Table 5.

Table 5 - Degradation data generated

Time	**Vibration**	**Pressure**	**Temperature**
1	3.98169174	288.8487682	30.03367903
2	3.983151725	294.604602	30.22461677
3	3.990086895	296.1360064	30.22193995
4	4.020296436	299.5239951	30.33781184
5	3.969380173	305.7219827	30.32858942
6	4.019620087	297.2013179	30.46524777
7	4.030546113	295.0971958	30.71748131
8	3.981904217	302.3701405	30.47947516
9	3.981960703	299.1000298	30.40389265
10	4.041807458	308.7555821	30.71096781
11	4.041893353	302.4518426	30.89565092
12	4.050312707	309.4125866	31.19613261
13	4.091938564	307.1383892	31.14060045
14	3.982217127	305.9876902	31.08357869
–	–	–	–
–	–	–	–
–	–	–	–

9997	35.63352717	18058.74032	804.9773486
9998	39.70433407	18294.08196	802.1708394
9999	37.95958325	18352.73953	792.4277949

Source: The author (2023)

3.7.1.1 Monte Carlo simulation pseudocode for variance gamma model

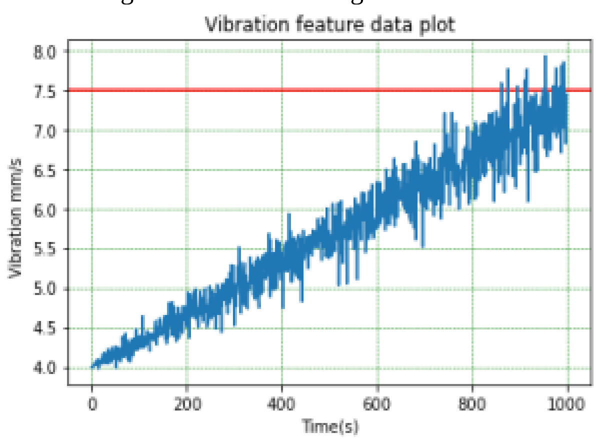
1. $X(0) = 0$
2. For $i = 1\ to\ n$

Generate the independent gamma process $\alpha_i^+(t), \alpha_i^-(t)$,

$X(t_i) = \alpha_i^+(t) - \alpha_i^-(t)$,

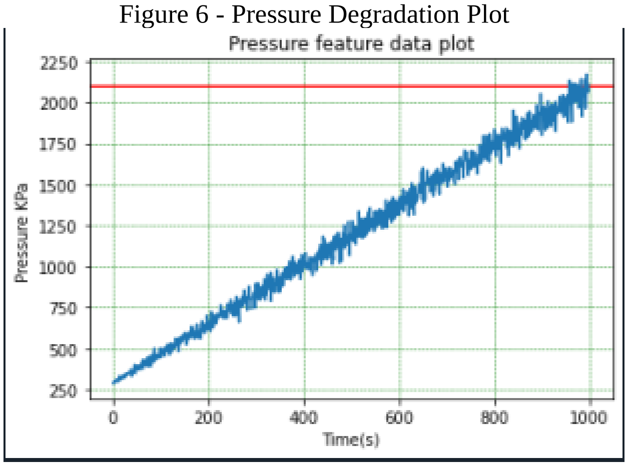
$X(t) = X(t_{i-1})$ for all $t \in (t_{i-1}, t_i)$.

Figure 5 - Vibration Degradation Plot



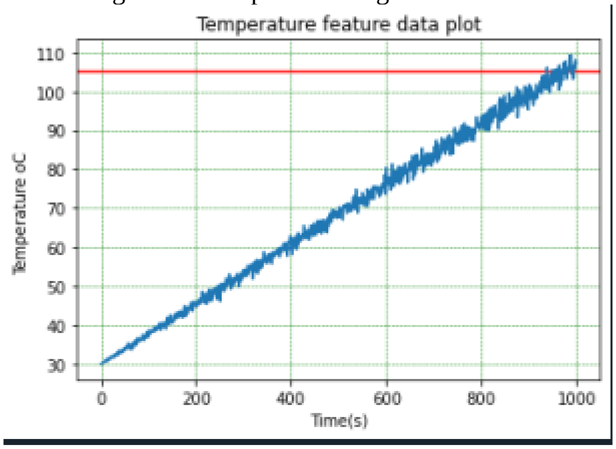
Source: The author (2023)

Figure 6 - Pressure Degradation Plot



Source: The author (2023)

Figure 7 - Temperature Degradation Plot



Source: The author (2023)

The gamma, Wiener, and variance gamma processes Wang et al. (2021), Ye, Chen and Shen (2015) and Mitra et al. (2022) are commonly employed for modeling degradation processes in mechanical systems. The linear distribution trend observed in Figures 5, 6, and 7 can be attributed to the specific parameter selections made. Different parameter sets would yield distinct behaviors. Nevertheless, it is noteworthy that certain systems employing the variance gamma process for degradation also exhibit a linear distribution trend, as evidenced in the works of Mitra et al. (2022), Shat and Schwabe (2019), Mahmoodian and Alani (2013) and Qidong and Dan (2014).

3.7.2 Development of the Reinforcement learning algorithm

General assumptions:

1. Periodic inspections of the pump are not considered, the pump can only be inspected whenever the RL agent makes a decision to stop it.
2. The cost of maintenance actions is constant and known- this determines the reward function
3. Each of the time step are defined as the interactions of the agent with the system
4. When all the performance indicators are in ‘good’ state, i.e., state ‘0’ then only the constant energy cost C_e is consumed.
5. In the case where the pump is in state 1, i.e., at least one of the performance indicators is in the degrading state, the energy cost becomes C_{em}. The maintenance cost, C_m, is accrued if the agent chooses to stop the pump for maintenance action.

6. If the pump is in state 2, i.e., at least one of the performance indicators is in the failed state, an imminent corrective action should therefore be performed. There is accrued the failure cost C_f.
7. In all cases, $C_p > C_f > C_m > C_r$

Reinforcement learning involves an agent solving an MDP problem which interacts with a simulated environment and acquires experience progressively to comprehend the long-term consequence of the actions and the value of visiting specific states. Therefore, before one can solve an RL problem, it has to be modelled as an MDP in respect to its state, action and reward spaces.

i. State space

The state space S_t comprises of the combination of the range in which the pressure SP_{t_i} temperature ST_{t_i}, and vibration SV_{t_i} levels of the pump present at each time step $t_i \ldots\ldots t_n$. This is inscribed as discrete variables as represented by:

$$S_t = \begin{matrix} SV_{t_1} & ST_{t_1} & SP_{t_1} \\ SV_{t_2} & ST_{t_2} & SP_{t_2} \\ \vdots & & \\ SV_{t_n} & ST_{t_n} & SP_{t_n} \end{matrix}$$

Where for example, $SV_{t_1} \ldots\ldots SV_{t_n}$ represents the discrete state of the pump's vibration at time t_i until t_n.

The acceptable range of operation for each state of the pump is depicted in each of the features as highlighted in Table 6, this determines the state space for the model

Table 6 - Thresholds for pump's state

Performance feature	**Good state** $SV_t, ST_t, SP_t = 0$	**Degrading state** $SV_t, ST_t, SP_t = 1$	**Failed state** $SV_t, ST_t, SP_t = 2$
Temperature	30°C – 100°C	101°C – 105°C	> 105°C
Pressure	280kPa – 2020kPa	2021kPa – 2100kPa	> 2100kPa
Vibration	4.0mm/s – 7.1mm/s	7.2mm/s – 7.5mm/s	> 7.5mm/s

Source: The Weir Group (2022)

ii Action space

The action space $a_n t$ is a vector consisting of n binary variables that indicate the type of maintenance action to be taken on the pump at each time step t.

This is expressed as:

$$a_n t = [a_1(t), a_2(t) \ldots\ldots a_n(t)]$$

Where, n refers to the number of possible actions in the set

In the case of this work, two actions are considered:

$$a_n t = \begin{cases} 0, keep\ running\ the\ pump \\ 1, stop\ for\ maintenance \end{cases}$$

iii Reward function

In order to allow the RL algorithm to learn well, a robust reward function for the agent must be modeled. This reward function will be in terms of cost and will be made up of the following components.

1. Energy cost (C_e): this is the cost incurred by energy consumption of the pump. It is the predicted cost for system operation, pump driver, controls and any auxiliary services.
2. Repair cost (C_r): this is the cost incurred by checking the pump if the agent decides to stop the pump even though it is in a functional state. Note: This cost is expected to be accrued in the beginning of training, as the agent learns more about the environment, such scenario to warrant this cost should not arise.
3. Maintenance cost (C_m): this is the cost incurred by a degrading pump.
4. Penalty cost (C_p): This is the cost incurred due to a wrong decision taken by the agent. This cost is accrued for a pump in state 2 wherein the agent chooses to continue its operation nevertheless. This cost is necessary to train the agent to make right decisions.
5. Failure cost (C_f): This is the cost incurred when the pump is stopped due to failure (made up of corrective maintenance cost, cost of lost time due to stoppage of production process)

Assumptions for the reward cost function

a. For a normal working pump, it consumes a constant unit of electricity for the time that the pump's vibration is within normal working limits.
b. When the pump's vibration exceeds a certain threshold, the energy consumption changes.
c. All other costs $C_m. C_r, C_p, C_f$ are constant and fixed.

iv Energy Cost

The effect of pump motor vibration on power quality and energy consumption has been studied. According to the work of Fetyan and El_Gazzar (2014), they studied the effect of motor vibration on the dynamic performance and electrical power quality of water pump stations comprising of axial flow pumps. Their results showed that the total harmonic distortion (THD) increases by about 1-2% due to the effect of bad motor vibration. The 5th and 7th harmonic contents also increased by about 0.5 – 1%. It was noted that the vibration above acceptable range causes dynamic troubles and some power quality problems for the electric feeder which results in flickers and variable energy consumption.

The summation of all harmonics in a system is known as THD. Associated Power Technologies (2012) explained the concept of THD and its effect on powered equipment. The harmonic contents and THD can be calculated by measuring the voltage and current signal and their values represent the status of power quality (FETYAN, EL_GAZZAR, 2014).

THD is given by Equation (3.2):

$$THD = \frac{\sqrt{{V_2}^2 + {V_3}^2 + {V_4}^2 + \cdots {V_n}^2}}{V_s} \tag{3.2}$$

Where, V_s = signal amplitude (RMS volts)

V_2= second harmonic amplitude (RMS volts)

V_n = nth harmonic amplitude (RMS volts)

Non-linear loads such as found in pumps are known to affect the power quality of a system. this is because they can draw current that is not perfectly sinusoidal, causing voltage waveform distortions. These unwanted distortions result usually erupt from an unfavorable increase in vibration levels (EBERSBACH, PENG, KESSISSOGLOU, 2006).

From the foregoing discussion, this work therefore assumes that when the pump's vibration exceeds the upper limit, for every 1% rise in the vibration level, the THD increases by 2% and results in an increase of energy consumption of 1%. Simulated data was generated and was fitted using the exponential distribution for the parameters. The power consumption P_c at a vibration level V_t above the acceptable limit is given by Equation (3.3):

$$C_{em} = [0.0144e^{0.2677V_t}] * u \tag{3.3}$$

Where, u is the unit cost of electricity.

The reward function is the addition of all the accumulated costs at each training time (t). The reward is negative because the agent is trying to minimize the cost. This is given in Equation (3.4)

$$R(t) = -\left[C_e(t) + C_r(t) + C_m(t) + C_f(t) + C_p(t)\right] \tag{3.4}$$

Where, $C_e(t) = \begin{cases} C_e, & Pump\ vibration\ is\ in\ good\ state \\ C_{em} & Otherwise \end{cases}$

3.7.3 Training the RL algorithm

The steps in training the Reinforcement learning algorithm involves two algorithms, the first algorithm is the Deep Q-Network (DQN) machine (shown in appendix A) and the second algorithm is the maintenance environment (shown in appendix B). It is noteworthy to mention that these 2 algorithms are interconnected. The DQN machine basically comprises of the deep neural network (DNN) and it is responsible for choosing the action in every time-step based on the observed state of the environment. The maintenance environment algorithm is responsible for simulating the behaviour of the system, such as the degradation process, the expected cost for each action, and calculating the rewards for the DQN algorithm. The DQN interacts with the environment to perform an offline training.

In the beginning, the DNN is randomly initialized. The maintenance environment starts by first expressing the features of the environment in their states. The performance features (vibration, temperature, and pressure) presented as continuous variables and then discretized to represent the state S_t at time t. The combination(s) of these features as states presents as the input to the learning interface.

These states are passed to the DNN in order to output the q value comprising of the state and the predicted action a_t as $q(S_t, a_t)$. The agent's experiences at each time step are stored in a replay memory where the agent's experience at time t is e_t defined as a tuple:

$$e_t = (S_t, a_t, r_{t+1}, S_{t+1})$$

Where, S_t is the state of the environment, and action a_t taken from state S_t. The reward r_{t+1} is gotten as a result of the previous state-action pair (S_t, a_t). The next environment state presented to the agent is denoted as S_{t+1}.The replay memory is set to a finite size limit N which is allowed at time t. A batch size is randomly sampled from the replay memory data known as experience replay. A key reason for using replay memory is to break the correlation between consecutive samples in order to avoid inefficient learning (BASU, 2020).

The input state data (batch) then propagates through the network and outputs an estimated q value for each possible action from the given state; the loss is calculated by comparing the q value output from the network in the experience tuple and the corresponding optimal q value or target q value for the same action in Equation (3.5).

$$q_*(S,a) \quad - \quad q(S,a) \quad = \quad loss$$

$$E[R_{t+1} + \gamma \max_{a'} q_\pi(s',a')] - E[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}] = loss \tag{3.5}$$

Target Q value - Output value = loss

The actions are initially chosen at random according to the epsilon parameter ε. The epsilon greedy ($\varepsilon - greedy$) method is deployed which is used to determine the agent's exploitation versus exploration trade-off. Rewards accumulated are subjected to rules guiding the action selected by the agent. These rules are highlighted on line 16 -29 of the pseudocode in the appendix. Each of the state transition per time step is governed by the variance gamma process degradation of the centrifugal pump. The agent is expected to make accurate action prediction as it is presented with the environment's next states. It is interesting to note that, because the initial actions of the agent are randomly chosen, wrong decisions may be taken, these are penalized with a penalty cost so as to train the agent in order to learn to take precise actions.

This training executes until the minimum epsilon is reached according to the decay rate. At the end of training, it is believed that the optimal policy must have been learned.

3.7.4 Parameter information

The parameter of the reward function costs is shown in Table 7.

Table 7: Parameter values for reward function

Parameter	**Value**
Repair cost C_r	10 Rs
Maintenance cost C_m	25 Rs
Failure cost C_f	50 Rs
Penalty cost C_p	100 Rs
Electricity consumption cost when operating within normal vibration limits C_e	0.05 Rs/unit

Source: The author (2023)

The hyperparameter information for the DQN machine and training stage is shown in Table 8

Table 8: Hyperparameters for DQN machine

Hyperparameter	**value**
Batch size B_s	200
*State size S_s	3
**Number of actions A_s	2
Learning rate L_r	0.0001
Epsilon decay ϵ_σ	0.9993
Minimum epsilon ϵ_m	0.0001
Gamma γ	0.95
Target steps T_s	10
Number of iterations	10000
Total time/iteration	1000

Source: The author (2023)

Note: * and ** are not hyperparameters for the training algorithm, they are determined according to the environment and problem to be solved respectively.

The training process was performed with 10,000 iterations each with 1000 time-steps. The RL-based CBM framework and decision environment were modelled in python 7.0 using Keras API.

3.7.5 Results and Discussions

Because RL algorithms seek to predict and control the effect of future value of taking an action or sequence of actions, it is pertinent to evaluate the results by analyzing the effect of the long-term accumulated rewards. Figure 8 shows the average accumulated reward over time.

Figure 8: Average Reward

Source: The Author (2023)

The simulation findings demonstrate that apart from the fact that the agent learnt the optimum policy over time, the accumulated reward over time exhibited a continuous improvement over the 10000 iterations initiated (fig 8). As the agent starts performing steps according to a random strategy epsilon = 1, it starts exploring the environment but gradually deploys the greedy strategy with a decay rate = 0.9993 until it performs exploitation after it learns more about its environment, this explains why the attained reward is minimal at the beginning of training. The initial reward was -56569, this improved over time to -1849. There is nevertheless a saturation at the end of the epochs (shown in the zoomed portion) which implies that the DQN cannot be improved anymore, this shows that the optimal policy has been learnt.

3.7.5.1 Sensitivity analysis

Due to the inadequacy of evaluating a trained agent solely on the reward received, a sensitivity analysis is necessary to ascertain the impact of changes in specific variables on the performance of the system as a whole. Bose et al. (2021) and Yao, Olson and Yoon (2021) employed sensitivity analysis in the field of RL to look at how the system can adapt to changes in the performance indicators of the goal function. A sensitivity analysis has eliminated the dependency on the possibility of an agent deploying a false policy by examining how an agent would respond to minor changes in its unpredictably changing environment.

To undertake the sensitivity analysis, the pump is simulated to degrade at 20% faster (20%++) and also at 20% slower (20%--) than the base degradation process. Each optimal policy for the different cases was saved. The optimal policies were deployed under an assumed time frame of 30days. The results were recorded and compared with the base degradation process. The comparison is done on the basis of the accumulated total cost and number of times the agent suggested a stoppage of the pump for inspection within the 30days.

The results of the sensitivity analysis are shown in Table 9

Table 9: Sensitivity Analysis Results

Case	parameters feature	parameters values				Result	
		θ	υ	μ	σ	Total cost	stoppages
Base case	Temperature	0.077	0.5	0.5	0.01	319	2
	Pressure	1.8	0.5	0.5	1.5		
	Vibration	0.0033	0.5	0.5	0.01		
20%++	Temperature	0.0924	0.5	0.5	0.012	366	5
	Pressure	2.16	0.5	0.5	1.8		
	Vibration	0.00396	0.5	0.5	0.012		
20%--	Temperature	0.0616	0.5	0.5	0.008	273	1
	Pressure	1.44	0.5	0.5	1.2		
	Vibration	0.00264	0.5	0.5	0.008		

Source: The Author (2023)

From table 9, it can be observed that, by increasing the degradation rate of the pump with 20%, the total cost accrued was 366 reais and the number of inspections predicted for the period of 30 days was 5. This result clearly shows that more maintenance cost and inspection is expected as the pump degrades faster. Similarly, a lower cost (273 reais) and one inspection is predicted for a slower degrading pump.

3.7.5.2 Benchmarking

The effectiveness of the proposed model was evaluated using a corrective policy as the benchmark. The performance of the corrective policy in each of the case scenarios presented in Table 9 was assessed based on the costs associated with operating the pump until it reaches failure. These costs were then compared to the total cost incurred by the reinforcement learning model under the same case scenarios. The comparative results are documented in Table 10.

Table 10: Reinforcement Learning and Corrective Maintenance cost comparison

Case	RL model cost	Corrective maintenance cost	Percentage performance
Base case	319	1043.2	69.4%
20%++	366	1143.2	68.0%
20%--	273	944.1	71.1%

Source: The Author (2023)

As depicted in Table 9, the analysis of the three scenarios reveals that the reinforcement learning policy yields cost savings of more than 68% compared to the corrective maintenance policy. This observation substantiates the superiority of the proposed policy in terms of cost effectiveness. The achieved improvements strongly indicate the successful adaptation of the maintenance policy for the centrifugal pump by the RL agent.

3.8 FINAL REMARKS ON THE CHAPTER

A new approach was introduced for optimizing the condition based-maintenance policy of a centrifugal pump used to transport slurry in an iron ore processing plant. The method's distinctiveness lies in the use of vibration, pressure and temperature features in the RL algorithm's environment state. Additionally, the system can function as an online control and monitoring tool for the pump's operation, allowing operators to anticipate potential failures. The proposed RL model was evaluated through sensitivity analysis to examine the influence of various variables on the system's performance. The results revealed the model's robustness, as it performed well under varying conditions of a faster or slower degrading pump. Comparison to a corrective maintenance strategy showed that the model can significantly lower maintenance costs. The model can therefore provide suggestions for immediate maintenance, predict future failures, and predict the number of pump stoppages in a specific time period. Future work will explore the application of the model to centrifugal pumps that operate in series or parallel, increasing the complexity of the system but still being feasible to achieve.

4 AN INTEGRATED OPPORTUNISTIC MAINTENANCE POLICY FOR A SET OF PRINCIPAL AND COLD STANDBY SYSTEM OF CENTRIFUGAL PUMPS USING THE DELAY-TIME CONCEPT

In this chapter an integrated opportunistic maintenance policy was developed. The system is composed of a principal set of pumps that operate continuously and a standby set that is activated in the event of failure from a pump in the principal set. To model the pump's degradation, the delay-time concept was utilized. An inspection and replacement policy (called KDM policy) was adopted for the principal system and an opportunistic and replacement (called ST policy) was developed for the standby set. The two policies were integrated as a KDMST policy, and their relationship and combined optimization were defined as the innovative aspect of this work. Simulation and sensitivity analysis results demonstrated a strong alignment with results from existing studies. Additionally, the proposed policy can be readily applied to other industries that utilize similar equipment.

4.1 PRIMARY AND BACKUP SYSTEM

A cold standby system is a sort of backup that is not actively in use but is kept in a ready state so that it can be triggered rapidly in the event of a primary system failure or disruption (WANG, XIONG, XIE, 2016). The primary functions of a cold standby system are to provide an alternative method for executing mission-critical tasks and to assure production continuity in the case of an unplanned failure (BEHBOUDI, MOHTASHAMI, ASADI, 2021). Due to these functions, its opportunistic maintenance is of the utmost importance. In standby systems, opportunistic maintenance is preferable over periodical maintenance because checks that are performed opportunistically rather than scheduled periodically may offer a financial advantage if opportunities are frequent and convenient (SCARF et al., 2009). This maintenance is crucial to guarantee proper redundancy, operating continuity, risk management, and compliance with industry rules and regulations (WANG et al., 2018). In a framework for a production system, the primary and backup systems can each take a configuration of either in series, parallel, or hybrid series-parallel. Each of these configurations adds a unique level to the system's reliability. A mixed arrangement utilizes the benefits of both the series and parallel configurations, although its implementation can be more difficult than any of the other two configurations (NANDA, KUNDU, NANDA, 2017). This work investigates the mixed arrangement i.e., (a series of parallel pumps) structure.

4.2 THE DELAY-TIME AS A METHOD FOR OPPORTUNISTIC MAINTENANCE ON STANDBY SYSTEMS

There are a variety of methods for performing opportunity maintenance on standby systems. These techniques are utilized to model the equipment's deterioration to optimize the maintenance policy. Notable among these techniques include the Semi-Markov process, Weiner process, Laplace Stieltjes transforms Mokaddis, Tawfek and Elhssia (1997), as well as the generative point technique Goel and Mumtaz (1994), which was used to predict the mean time to system breakdown, availability, and busy period for a cold standby system. The Weiner technique was utilized to characterize the system's degradation pattern (MA et al., 2020). Markov chains are often used to define the probability of transitioning between various system states and the costs associated with each transition (HAJEEH, 2014; MENDES, RIBEIRO, COIT, 2017; MENDES, RIBEIRO, 2017; ALEBRANT, COIT, DUARTE, 2014). In the literature, the delay-time concept is regarded as a more flexible and accurate model for predicting the degradation and failure of equipment (LIU et al., 2015). In addition to its adaptability and simplicity, the delay-time model takes into account the possibility that the rate of degradation of a system or component may not be constant over time (CRESPO, SA ANCHEZ HEGUEDAS, 2002). Contrary to this, the Markov chain model assumes that the rate of deterioration is constant (JOHN, MELVIN, 1997). The delay-time approach permits the incorporation of external factors that may affect the probability of failures, such as component maintenance, repair, or replacement (NAZEMI, 2018). Finally, it can estimate the time to failure of a system or component with greater accuracy than the Markov chain model, which simply provides probabilities of failure at certain time intervals. Examples of works employing the delay-time idea in opportunistic maintenance models are Lu et al. (2012), Scarf et al. (2009) and Wang, (2011).

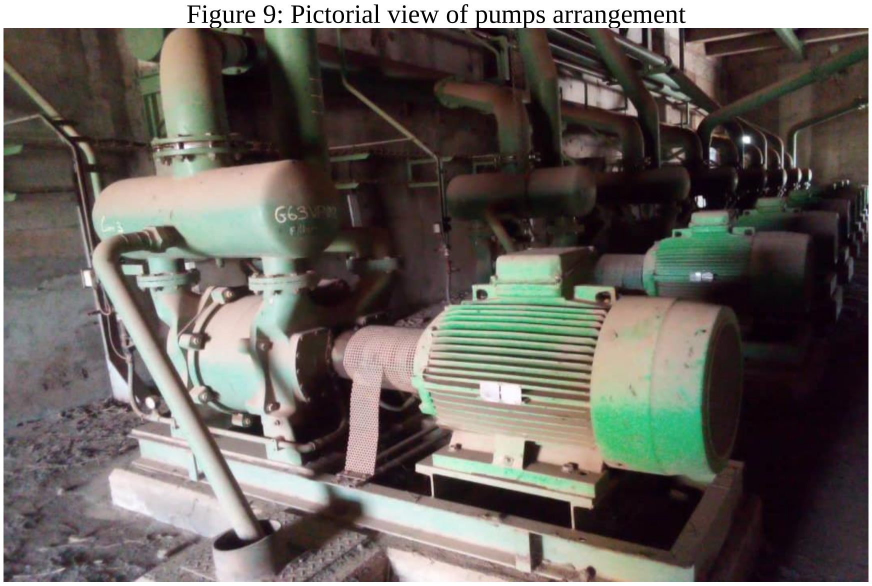
4.3 MAJOR CONTRIBUTION AND KNOWLEDGE GAP

Although studies have developed opportunistic maintenance on primary and standby systems separately using the delay-time concept systems (JIA et al., 2022; JIA et al., 2017; LEVITIN, FINKELSTEIN, DAI, 2020). To the best of the author's knowledge none have proposed an integrated policy for these two systems, which is how the innovation of this study is described. Therefore, this study distinguishes itself by proposing an integrated maintenance policy that considers actions for the principal system and for the standby system as well. The timing of actions, such as replacement, inspection, and failure times, is taken into consideration in the delay time model used to model the system's degradation. This is necessary in order to build a robust opportunistic maintenance policy. The numerical case is applied to two series-connected sets of centrifugal pumps, one of which is the primary system and the other the backup system.

4.4 THE DETAILED PROBLEM STATEMENT

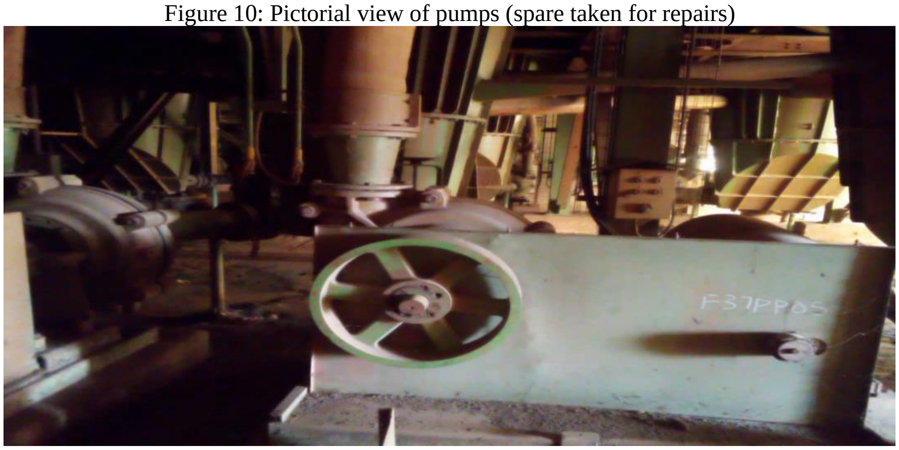
The production line of the company is composed of several equipment which receives slurry through centrifugal pumps. Please see Figures 9-11 for pictorial views of the pump arrangements in the industry. There exist two (2) sets of centrifugal slurry pumps as shown in the block diagram in Figure 12 as part of the process plant. The principal pumps are in series. This means that if any of the principal pump fails, the production system is halted. Each of the principal pump is connected to its spare pump in a parallel configuration, therefore, the system is a series of parallel system. The first set is referred to as the principal system (set A) and the second set is called the standby (set B). The 'set A' comprises of the main functional pumps that run at all time to enable smooth production. The main components of these sets of pumps that causes frequent stoppages are the internal components such as; the gland seal, packing seal and the wear rings (FLSMIDTH, 2020). These internal components perform significant function in the slurry pump because they separate the slurry from the external environment when the process pressure and temperature are high in the industry under investigation. This demonstrates that when temperature and pressure rise above a particular point, any of these components can collapse (RIDGWAY et al., 2009). In the arrangement of the set of pumps, when the pump in a set fails, it triggers a demand with rate μ on the corresponding alternate pump. Considering a simple case, if pump A1 fails, pump B1 takes over its functionality (see figure 14). Hence, the failure of pump A1 creates a demand for pump B1. Also, all preventive actions for pump A2 will create an opportunity with rate λ to perform inspection on pump B1. Because of this incident, pump B1 should always be available for swap as long as its conditions for functionality are favourable. This defines a typical preparedness system. A preparedness system is a system that is required to function only on-demand as in the case of an emergency (CAVALCANTE, SCARF, ALMEIDA, 2011). It is assumed that, at any point in time after a threshold S, an action on pump A2 provides an opportunity to inspect pump B1. The functional pump A2 should provide an opportunistic inspection (OI) to access the functionality of the spare pump B1. Therefore, there is the dire need to develop an inspection policy that will assist in identifying the state of the critical component of the spare system, determine the maximum number of inspections and interval between inspections for the principal system and also, determine the window of opportunity for inspection on the gland seal for the spare system. Therefore, there is the need to develop two maintenance policies. One focused on main systems and the other on spare systems. The integration of these two policies being of paramount importance. A more detailed description of these policies is provided in the next section.

Figure 9: Pictorial view of pumps arrangement



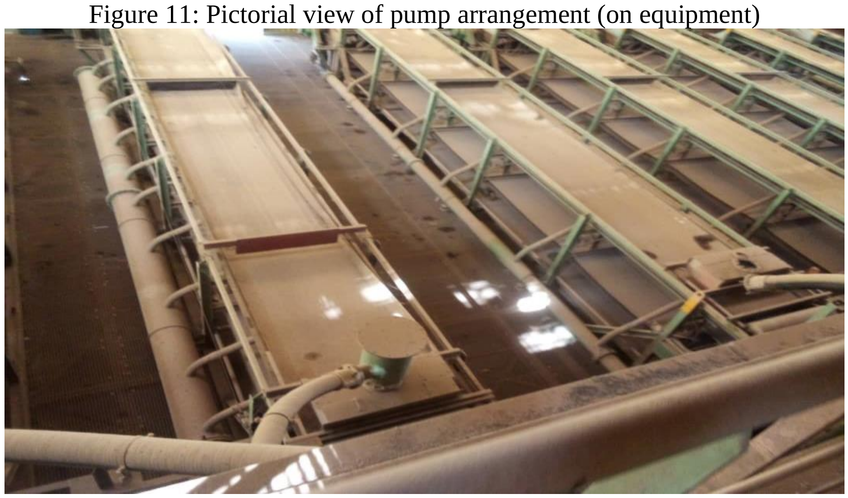
Source: The Author (2023)

Figure 10: Pictorial view of pumps (spare taken for repairs)



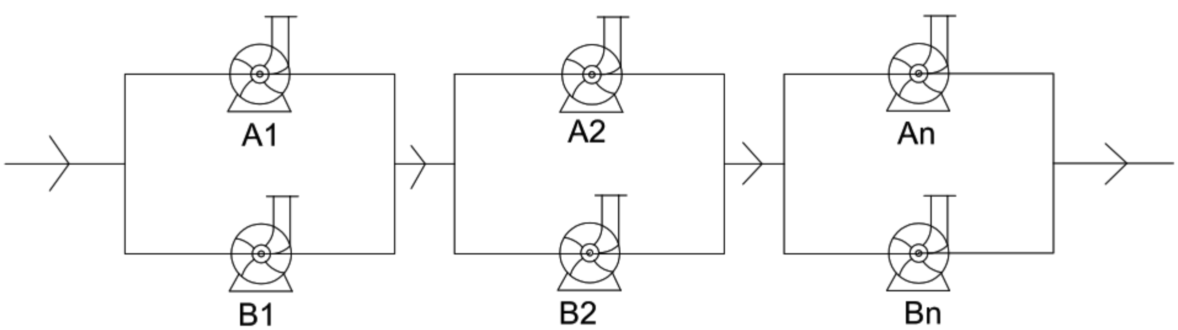
Source: The Author (2023)

Figure 11: Pictorial view of pump arrangement (on equipment)



Source: The Author (2023)

Figure 12: Setup of Centrifugal Pumps (Block diagram)

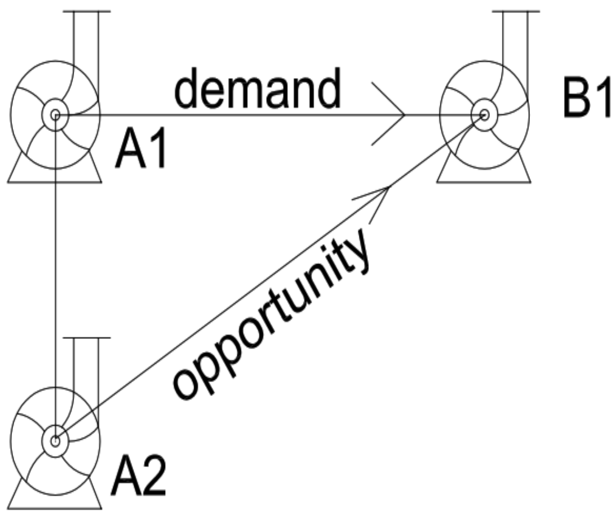


Source: The Author (2023)

Figure 13: Internal components (gland seal, packing seal and wear rings)

Source: The Author (2023)

Figure 14: Simple case problem definition



Source: The Author (2023)

4.5 SYSTEM DESCRIPTION

Table 11 presents the notation used in this chapter

Table 11: Notations

X	Age of spare part at defect arrival
H	Delay-time from arrival of defect until subsequent failure
L	Mean delay-time
s	Parameter of mixture, s=weak spare parts; (1-s) = strong spare parts
K	Number of inspections in a renewal cycle for principal system

D	Interval between inspections for principal system
M	Time until preventive maintenance for principal system.
T_R	Time required for preventive replacement on principal system
T_i	Time required for inspection on principal system
T_F	Time required for corrective replacement on principal system
W	Opportunity arrival for spare system
S	Window of opportunity for spare system
T	Time until preventive replacement for spare system
z	Arrival of demand in the spare system
μ	Rate of demand for the spare system
λ	Rate of opportunity for spare system
τ_1, τ_2	Characteristic life for spare part from sub-population, 1= weak spares, 2= strong spares
β_1, β_2	Shape parameter of probability distribution function *(pdf)* from sub-population.
f(x)	*pdf* of X
f(h)	Pdf of H
F_H	Cumulative distribution function *(cdf)* of H
f(z)	*pdf* of z
F_z	*cdf* of z
f(w)	*pdf* of w
F_w	*cdf* of w
C_I	The cost of inspection
C_R	The cost of preventive replacement
C_F	The cost of corrective replacement
C_{UD}	The cost of unmet demands
C_O	The cost of opportunity maintenance
EL	Expected length of a renewal cycle
EC	Expected cost of a renewal cycle

$C_{\infty p}$	Cost-rate (expected cost per unit of time in the long-run) for principal system
$C_{\infty s}$	Cost-rate (expected cost per unit of time in the long-run) for spare system

Source: The Author (2023)

4.5.1 Numerical case

Consider a simple case of a centrifugal pump. This pump is defined as a single component, which provides an operational function for smooth production process. According to Sinisterra et al. (2023) and Christer (1999), it is postulated that an equipment can exist in one of three possible states: namely, good, defective, or failed. The pump operates in either the good or defective state, which requires an inspection to distinguish between the two. This differentiation is established using the delay-time concept, as defined by Christer (1999). Two random variables, sojourn X in a good state and H in a defective state, exist and are distributed according to a known distribution. Additionally, it is presumed that the spare part requirement, i.e., the internal components can originate from a mixed population of products, consisting of a sub-population relating to the proportion of good spares (s) and the remainder comprising bad spares $(1 - s)$. The mixed population is defined as $F_x(x) = sf_a(x) - (1 - s)f_b(x)$, where, $f_a(x)$ and $f_b(x)$ respectively follow Weibull distribution with characteristic lives τ_1, τ_2 and shape β_1, β_2 .We consider a time of actions for replacement of spare parts T_R, inspection of the pump T_i, and the down time due to failure T_F, in the delay time model for the principal system. Each of these times of actions eventually affects the expected life of the system. Periodic inspections are assumed to be perfect. The gland seal is replaced instantaneously with a cost of C_R. A preventive replacement of this spare occurs at the critical replacement age T with a cost of C_F, where, $C_R < C_F$.

In the case of the set of spare pumps (cold standby system), we assume that the failure of an alternate pump in the principal set presents a demand μ for its corresponding spare pump in the spare set. This demand is only met if the spare pump is in the good, or defective state. Which means that the spare pumps can be in the good, defective or failed state, where the failure is not self-announced. There exists a rate of opportunity λ, to verify the alternate spare pump's condition. At any replacement (corrective or opportunity maintenance), the system is renewed to as-good-as-new. Therefore, inspections are perfect, and in the case of the spare system, maintenance action times are neglected. The cost of preventive replacement, opportunity maintenance, unmet demands and corrective replacement are given as C_R, C_O, C_{UD}, and C_F respectively. Where, $C_O < C_R < C_F < C_{UD}$.

4.6 MODEL

For the principal system, the model follows the established model of Scarf et al. (2009) for a replacement policy for heterogeneous components. For this model, it is called a KDM model. $K, D, and\ M$ are the decision variables, where, K represents the number of inspections in a renewal cycle, D represents the interval between inspections and M gives the time until a preventive maintenance is required. The details of the systems' equations for the probabilities for each case scenario, expected life and expected cost are explained below. Please note, for all cases, the length h is always denoted as the distance between the arrival of defect *x* and the failure.

Case A: The defect arrives in the ith interval between inspections and it is identified at the next inspection (Figure 15). The probability of the renewal cycle is given in Equation (4.1)

$$P_1(K, D, M) = \sum_{i=1}^{K} \int_{(i-1)\Delta}^{i\Delta} f(x)\big(1 - F_H(i\Delta - x)\big)dx \tag{4.1}$$

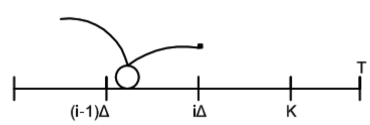
The expected length of the renewal cycle is associated with T_R and iT_i. This is shown in Equation (4.2)

$$EL_1(K, D, M) = \sum_{i=1}^{K} i\Delta + T_R + iT_i \int_{(i-1)\Delta}^{i\Delta} f(x)\big(1 - F_H(i\Delta - x)\big)dx \tag{4.2}$$

The expected cost is associated with the cost of inspection and cost of preventive replacement (Equation 4.3)

$$EC_1(K, D, M) = (iC_I + C_R) * P_1(K, D, M) \tag{4.3}$$

Figure 15: KDM model-Case A



Source: Adapted from Scarf et al. (2009)

Case B: The defect and failure occur in the ith interval between inspections (Figure 16). This is why the first integral is in the range of $i\Delta$ and $(i - 1)\Delta$ as shown in Equation (4.4) of the probability of the renewal cycle.

$$P_2(K,D,M) = \sum_{i=1}^{K} \int_{(i-1)\Delta}^{i\Delta} \int_{0}^{i\Delta - x} f(h)f(x)dhdx \tag{4.4}$$

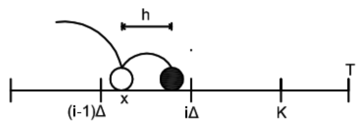
The expected length of renewal cycle is given in Equation (4.5)

$$EL_2(K,D,M) = \sum_{i=1}^{K} (T_F + (i-1)T_i \int_{(i-1)\Delta}^{i\Delta} \int_{0}^{i\Delta - x} (x+h)f(h)f(x)dhdx \tag{4.5}$$

The expected cost is given in Equation (4.6)

$$EC_2(K,D,M) = \big((i-1)C_I + C_F\big) * P_2(K,D,M) \tag{4.6}$$

Figure 16: KDM model – case B



Source Adapted from Scarf et al. (2009)

Case C: in case C, the defect and failure occur after $K\Delta$ and before T (Figure 17). The probability of the renewal cycle is given in Equation (4.7) and the expected length of the renewal cycle is in Equation (4.8)

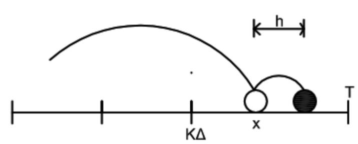
$$P_3(K,D,M) = \sum_{i=1}^{K} \int_{K\Delta}^{T} \int_{0}^{T-x} f(h)f(x)dhdx \tag{4.7}$$

$$EL_3(K,D,M) = \sum_{i=1}^{K} (KT_i + T_F) \int_{K\Delta}^{T} \int_{0}^{T-x} (x+h)f(h)f(x)dhdx \tag{4.8}$$

The expected cost becomes Equation 4.9

$$EC_3(K,D,M) = (KC_I + C_F) * P_3(K,D,M) \tag{4.9}$$

Figure 17: KDM model – case C



Source: Adapted from Scarf et al. (2009)

Case D: here, the defect arrives after $K\Delta$ and it is identified at T (Figure 18). The probability of the renewal cycle is given in Equation (4.10)

$$P_4(K,D,M) = \sum_{i=1}^{K} \int_{(K\Delta}^{T} f(x)\big(1 - F_H(T-x)\big)dx \tag{4.10}$$

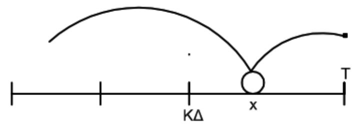
Equation (4.11) depicts the expected length of the renewal cycle

$$EL_4(K,D,M) = \sum_{i=1}^{K} T + T_R + KT_i \int_{K\Delta}^{T} f(x)\big(1 - F_H(i\Delta - x)\big)dx \tag{4.11}$$

The expected cost is in Equation 4.12

$$EC_4 = (KC_I + C_R) * P_4(K,D,M) \tag{4.12}$$

Figure 18: KDM Model- case D



Source: Adapted from Scarf et al. (2009)

Case E: In this case, there is no defect and the system is replaced preventatively at T (Figure 19). This is why the outer boundary integral in the probability equation is infinity (Equation 4.13). The expected length of the renewal cycle is given in Equation 4.14

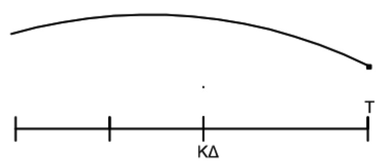
$$P_5(K,D,M) = \int_T^{\infty} f(x)dx \quad (4.13)$$

$$EL_5(K,D,M) = \sum_{i=1}^{K} T + T_R + KT_i \int_T^{\infty} f(x)dx \quad (4.14)$$

And the expected cost is given in Equation (4.15)

$$EC_5 = (KC_I + C_R) * P_5(K,D,M) \quad (4.15)$$

Figure 19: KDM Model- case E



Source: Adapted from Scarf et al. (2009)

The long-run cost per life is minimized as given in Equation (4.16):

$$C_{\infty}(K,D,M) = \frac{\sum_{i=1}^{5} EC_i(K,D,M)}{\sum_{i=1}^{5} EL_i(K,D,M)} \quad (4.16)$$

According to Scarf et al. (2009), the probability that a cycle ends in failure, rho, is given by Equation (4.17)

$$rho = P_1(K,D,M) + P_3(K,D,M) \quad (4.17)$$

And the mean time between failures (MTBOF) for the gland seals (Equation 4.18) becomes:

$$MTBOF = \frac{\sum_{i=1}^{5} EL_i(K,D,M)}{rho} \quad (4.18)$$

For the spare system called the ST policy, 20 scenario cases were modelled. Each of these 20 cases are described as follows.

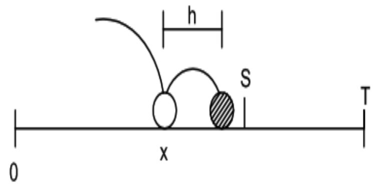
Case 1: The defect and failure arrive before S. There is no demand between $(x+h)$ and T, no opportunity until a corrective replacement at T (Figure 20). The probability of the renewal cycle is given as Equation (4.19):

$$P_1(S,T) = \int_0^S f(x) \int_0^{S-x} f(h)\,[1 - \int_{x+h}^{T} f(z)dz]dhdx\,[1 - \int_s^T \mu e^{-\mu(w-s)}dw] \quad (4.19)$$

The expected life is the product of the time until preventive maintenance and the probability is $EL_1(S,T) = T * P_1(S,T)$.

The expected cost is associated with the cost of failure, since a failure existed in the cycle, $EC_1(S,T) = C_F * P_1(S,T)$.

Figure 20: ST model – case 1



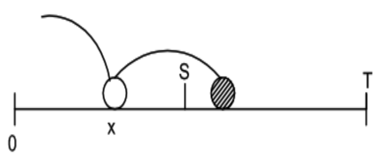
Source: This research (2023)

Case 2: In case 2, there is a defect before S and a failure between S and T. There is no demand between $(x + h)$ and T, no opportunity until a corrective replacement at T (Figure 21). Hence the probability of a renewal cycle follows in Equation (4.20)

$$P_2(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \, [1 - \int_{x+h}^T f(z)dz]dhdx \, [1 - \int_s^T \mu e^{-\mu(w-s)} dw] \qquad (4.20)$$

The length of the cycle is $EL_2(S,T) = T * P_2(S,T)$, and the expected cost is $EC_2(S,T) = C_F * P_2(S,T)$

Figure 21: ST Model- case 2



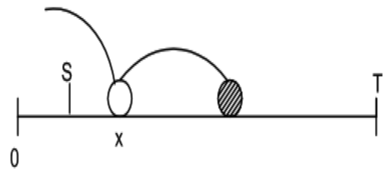
Source: This research (2023)

Case 3: Defect and failure exist between S and T. there is no demand between $(x + h)$ and T. No opportunity until corrective replacement at T (Figure 22). Equation (4.21) shows the probability of the renewal cycle.

$$P_3(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \, [1 - \int_{x+h}^T f(z)dz]dhdx \, [1 - \int_s^T \mu e^{-\mu(w-s)} dw] \qquad (4.21)$$

The expected length of the renewal cycle and its associated cost are given as $EL_3(S,T) = T * P_3(S,T)$ and $EC_3(S,T) = C_F * P_3(S,T)$ respectively.

Figure 22: ST Model- case 2



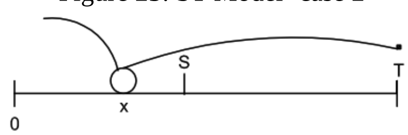
Source: This research (2023)

Case 4: In case 4; there is a defect before S. No opportunity and failure. Preventive replacement at T. In a case like this, demand may arrive, but it does not change anything as the defective state meets demand (Figure 23). The cycle's probability is given in Equation 4.22

$$P_4(S,T) = \int_0^S f(x) \int_{T-x}^{\infty} f(h)dhdx\, [1 - \int_s^T \mu e^{-\mu(w-s)}dw] \quad (4.22)$$

The expected length of the renewal cycle is $EL_4 = T * P_4(S,T)$ and its associated cost is given as $EC_4 = C_F * P_4(S,T)$.

Figure 23: ST Model- case 2



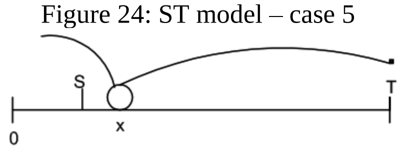
Source: This research (2023)

Case 5: In case 5; there is a defect between S and T. there is no demand, opportunity or failure. But there is a preventive replacement at T (Figure 24). Equation (4.23) shows the probability of the renewal cycle

$$P_5(S,T) = \int_S^T f(x) \int_{T-x}^{\infty} f(h)dhdx\, [1 - \int_s^T \mu e^{-\mu(w-s)}dw] \quad (4.23)$$

The length of the renewal cycle is $EL_5(S,T) = T * P_5(S,T)$ and the expected cost is $EC_5(S,T) = C_R * P_5(S,T)$.

Figure 24: ST model – case 5



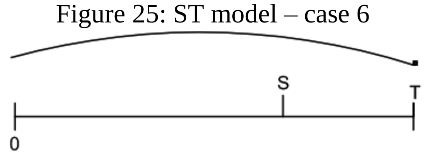
Source: This research (2023)

Case 6: In case 6; there is no defect arrival in the cycle, except a preventive replacement at T (Figure 25). Its cycle's probability is given as Equation (4.24)

$$P_6(S,T) = \int_T^{\infty} f(x)\, [1 - \int_s^T \mu e^{-\mu(w-s)}dw] \quad (4.24)$$

The expected length is $EL_6(S,T) = T * P_6(S,T)$. Also, the expected cost is $EC_6(S,T) = C_R * P_6(S,T)$

Figure 25: ST model – case 6



Source: This research (2023)

Case 7: In case 7; there is defect and failure before S. Demand between $(x+h)$ and S (Figure 26). No opportunity until a corrective replacement at z. The probability of the renewal cycle is given in Equation (4.25)

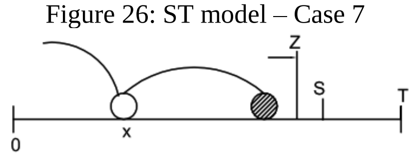
$$P_7(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_{x+h}^{S} f(z)\, dzdhdx \tag{4.25}$$

The expected length of cycle in this case is given as Equation (4.26)

$$EL_7(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_{x+h}^{S} zf(z)\, dzdhdx \tag{4.26}$$

The expected cost is associated with the cost of unmet demand, $EC_7(S,T) = C_{UD} * P_7(S,T)$ because the demand was not met before the cycle ended.

Figure 26: ST model – Case 7



Source: This research (2023)

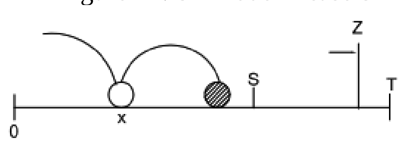
Case 8: In case 8; there is defect and failure before S. Demand between S and T. No opportunity between S and z until a corrective replacement at z (Figure 27). The probability of the renewal cycle and its length are shown in Equation (4.27) and (4.28) respectively

$$P_8(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_S^T f(z)\, [1 - \int_s^z \mu e^{-\mu(w-s)} dw] dzdhdx \tag{4.27}$$

$$EL_8(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_S^T zf(z)\, [1 - \int_s^z \mu e^{-\mu(w-s)} dw] dzdhdx \tag{4.28}$$

The expected cost is given as $EC_8(S,T) = C_{UD} * P_8(S,T)$.

Figure 27: ST model – case 8



Source: This research (2023)

Case 9: In case 9; there is defect and failure after S. Demand also exists between $(x + h)$ and T. however, there is no opportunity between S and z until a corrective replacement at z (Figure 28). Hence the probability of the renewal cycle is given as Equation (4.29)

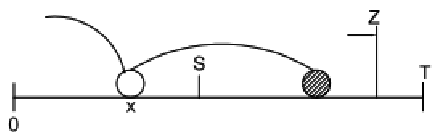
$$P_9(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_{x+h}^T f(z) \left[1 - \int_s^z \mu e^{-\mu(w-s)} dw\right] dz dh dx \tag{4.29}$$

And the expected length is shown as Equation (4.30)

$$EL_9(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_{x+h}^T z f(z) \left[1 - \int_s^z \mu e^{-\mu(w-s)} dw\right] dz dh dx \tag{4.30}$$

The expected cost is $EC_9(S,T) = C_{UD} * P_9(S,T)$.

Figure 28: ST model – case 9



Source: This research (2023)

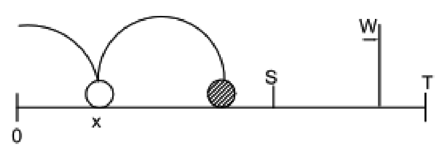
Case 10: In case 10; there is defect and failure before S. No demand between $(x + h)$ and w but there is corrective replacement due to an opportunity at w (Figure 29). The probability of cycle renewal and the expected length of the renewal cycle is written in Equation (4.31) and (4.32) respectively

$$P_{10}(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_S^T \mu e^{-\mu(w-s)} \left[1 - \int_{x+h}^w f(z) dz\right] dw dh dx \tag{4.31}$$

$$EL_{10}(S,T) = \int_0^S f(x) \int_0^{S-x} f(h) \int_S^T w * \mu e^{-\mu(w-s)} \left[1 - \int_{x+h}^w f(z) dz\right] dw dh dx \tag{4.32}$$

The expected cost is associated with the cost of opportunity as $EC_{10}(S,T) = C_O * P_{10}(S,T)$.

Figure 29: ST model – case 10



Source: This research (2023)

Case 11: In case 11; there is a defect before S but an opportunity prevents failure between S and T (Figure 30). The renewal's cycle probability is given in Equation (4.33)

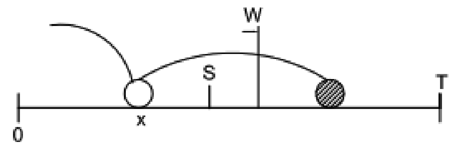
$$P_{11}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_S^{x+h} \mu e^{-\mu(w-s)} dw dh dx \tag{4.33}$$

And the expected length is shown in Equation (4.34) below

$$EL_{11}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_S^{x+h} w * \mu e^{-\mu(w-s)} dw dh dx \tag{4.34}$$

The expected cost is associated with the cost of opportunity as, $EC_{11}(S,T) = C_O * P_{11}(S,T)$.

Figure 30: ST model – case 11



Source: This research (2023)

Case 12: In case 12; there is defect arrival before S, however the failure occurs between S and T. An opportunity at w prevents an unmet demand. There is no demand between $(x+h)$ and w. (Figure 31). The probability of renewal cycle is modelled in Equation (4.35).

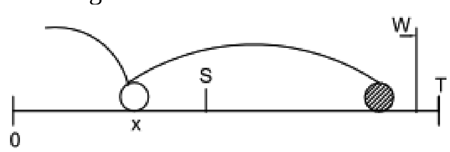
$$P_{12}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_{x+h}^{T} \mu e^{-\mu(w-s)} [1 - \int_{x+h}^{w} f(z)dz] dwdhdx \quad (4.35)$$

And the cycle's expected length is given in Equation 4.36

$$EL_{12}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_{x+h}^{T} w * \mu e^{-\mu(w-s)} [1 - \int_{x+h}^{w} f(z)dz] dwdhdx \quad (4.36)$$

Hence, the associated expected cost becomes $EC_{12}(S,T) = C_O * P_{12}(S,T)$.

Figure 31: ST model – case 12



Source: This research (2023)

Case 13: in case 13; there is an opportunity after S, but before the defect and failure. In this case, however, since there is no defect present, there is no replacement. However, since the arrival distribution of defects is exponential, it is similar to a renewal on opportunity (Figure 32). The probability of cycle renewal is given in Equation (4.37).

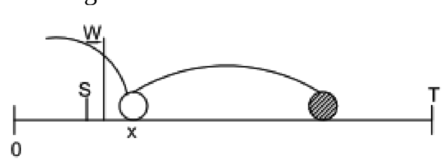
$$P_{13}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_S^{x} \mu e^{-\mu(w-s)} dwdhdx \quad (4.37)$$

The expected length of cycle is in Equation xx

$$EL_{13}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_S^{x} w * \mu e^{-\mu(w-s)} dwdhdx \quad (4.38)$$

The expected cost is associated with the cost of opportunity as $EC_{13}(S,T) = C_O * P_{13}(S,T)$.

Figure 32: ST model – case 13



Source: This research (2023)

Case 14: In case 14, there is a defect after S but the arrival of an opportunity an opportunity at w prevents the failure (Figure 33). Equation (4.39) shows the probability of a renewal cycle

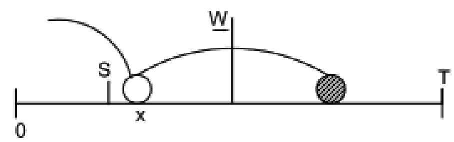
$$P_{14}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_x^{x+h} \mu e^{-\mu(w-s)} dwdhdx \quad (4.39)$$

The expected length of the cycle is written in Equation (4.40)

$$EL_{14}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_x^{x+h} w * \mu e^{-\mu(w-s)} dwdhdx \quad (4.40)$$

The expected cost is given as $EC_{14}(S,T) = C_O * P_{14}(S,T)$.

Figure 33: ST model – case 14



Source: This research (2023)

Case 15: In case 15; there is defect and failure after S. An opportunity at w prevents an unmet demand, also, there is no demand between $(x+h)$ and w (Figure 34). The probability of the renewal cycle is given in Equation (4.41)

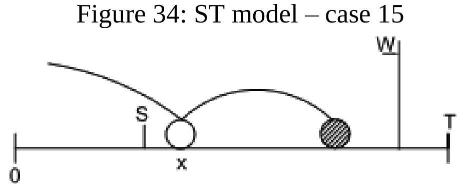
$$P_{15}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_{x+h}^{T} \mu e^{-\mu(w-s)} [1 - \int_{x+h}^{w} f(z)dz] dwdhdx \quad (4.41)$$

Its expected length of the renewal cycle is in Equation (4.42)

$$EL_{15}(S,T) = \int_S^T f(x) \int_0^{T-x} f(h) \int_{x+h}^{T} w * \mu e^{-\mu(w-s)} [1 - \int_{x+h}^{w} f(z)dz] dwdhdx \quad (4.42)$$

The expected cost is associated with the cost of opportunity and written as, $EC_{15}(S,T) = C_O * P_{15}(S,T)$.

Figure 34: ST model – case 15



Source: This research (2023)

Case 16: In case 16; there is a defect before S which does not lead to a failure. Therefore, there is a preventive replacement due to an opportunity (Figure 35). The probability of the renewal cycle is given in Equation (4.43)

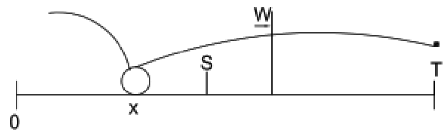
$$P_{16}(S,T) = \int_0^S f(x) \int_{T-x}^{\infty} f(h) \int_S^T \mu e^{-\mu(w-s)} dwdhdx \quad (4.43)$$

The expected length is given in Equation (4.44).

$$EL_{16}(S,T) = \int_0^S f(x) \int_{T-x}^{\infty} f(h) \int_S^T w * \mu e^{-\mu(w-s)} dwdhdx \quad (4.44)$$

The expected cost is $EC_{16}(S,T) = C_O * P_{16}(S,T)$.

Figure 35: ST model – case 16



Source: This research (2023)

Cases 17 and 18 depicts the arrival of an opportunity before and after a defect respectively, and also the defect in both cases arriving after S (Figures 36 and 37 respectively). The probabilities of the renewal cycle are shown in Equation (4.45) and (4.46) for cases 17 and 18 respectively.

$$P_{17}(S,T) = \int_S^T f(x) \int_{T-x}^{\infty} f(h) \int_S^x \mu e^{-\mu(w-s)} dwdhdx \tag{4.45}$$

$$P_{18}(S,T) = \int_S^T f(x) \int_{T-x}^{\infty} f(h) \int_x^T \mu e^{-\mu(w-s)} dwdhdx \tag{4.46}$$

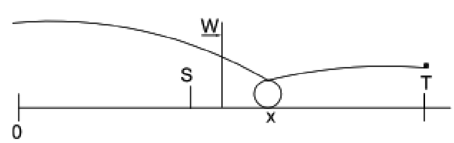
The corresponding expected lengths of the renewal cycle are depicted in Equation (4.47) for case 17 and Equation (4.48) for case 18.

$$EL_{17}(S,T) = \int_S^T f(x) \int_{T-x}^{\infty} f(h) \int_S^x w * \mu e^{-\mu(w-s)} dwdhdx \tag{4.47}$$

$$EL_{18}(S,T) = \int_S^T f(x) \int_{T-x}^{\infty} f(h) \int_x^T w * \mu e^{-\mu(w-s)} dwdhdx \tag{4.48}$$

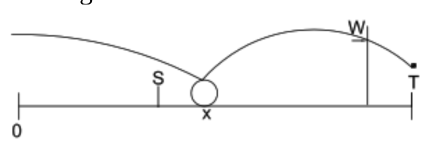
The expected costs are both associated with the cost of opportunity given as, $EC_{17}(S,T) = C_O * P_{17}(S,T)$ for case 17 and $EC_{18}(S,T) = C_O * P_{18}(S,T)$ for case 18.

Figure 36: ST model – case 17



Source: This research (2023)

Figure 37: ST model – case 18



Source: This research (2023)

Case 19: Case 19 shows the scenario of the arrival of no defect, but a negative inspection due to an opportunity (Figure 38). Its probability of renewal cycle is given in Equation (4.49)

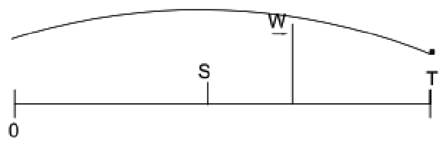
$$P_{19}(S,T) = \int_T^{\infty} f(x) \int_S^T \mu e^{-\mu(w-s)} dw dx \tag{4.49}$$

The expected length of the renewal cycle is given in Equation (4.50)

$$EL_{19}(S,T) = \int_T^{\infty} f(x) \int_S^T w * \mu e^{-\mu(w-s)} dw dx \tag{4.50}$$

The expected cost therefore becomes, $EC_{19}(S,T) = C_O * P_{19}(S,T)$.

Figure 38: ST model – case 19



Source: This research (2023)

Finally, in **case 20,** there is a defect before S. Failure comes between S and T. There is the arrival of a demand between $(x+h)$ and T and no opportunity between S and z (Figure 39). The probability of renewal cycle is as in Equation (4.51)

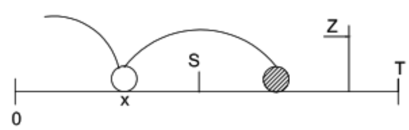
$$P_{20}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_{x+h}^T f(z)[1 - \int_S^z \mu e^{-\mu(w-s)} dw] dz dh dx \tag{4.51}$$

The associated expected length of renewal cycle is given in Equation (4.52)

$$EL_{20}(S,T) = \int_0^S f(x) \int_{S-x}^{T-x} f(h) \int_{x+h}^T z * f(z)[1 - \int_S^z \mu e^{-\mu(w-s)} dw] dz dh dx \tag{4.52}$$

And the expected cost is a function of the cost of unmet demand, $EC_{20}(S,T) = C_{UD} * P_{20}(S,T)$.

Figure 39: ST model – case 20



Source: This research (2023)

The integrated optimized cost rate (Equation 4.53) is given as the ratio of the total expected costs of the two policies (KDM) and (ST) to their total expected life.

$$C_{\infty}(K,D,M,S,T) = \frac{\sum_{i=1}^{5} EC_i(K,D,M) + \sum_{i=1}^{20} EC_i(S,T)}{\sum_{i=1}^{5} EL_i(K,D,M) + \sum_{i=1}^{20} EL_i(S,T)} \tag{4.53}$$

It is considered that the internal component of the centrifugal pump has a characteristic life τ_2 of 5 years for the strong spares (WEIR, 2000). The mean time between failures (MTBOF) of the seal component was retrieved from the result of the optimized decision variables of the principal system (KDM) and used to calculate the rate of demand as ($\mu = \frac{1}{MTBOF}$).

The KDM model yields an MTBOF value of 8.0908, implying an anticipated failure rate of the gland seal approximately once every 8 years. To enhance the realism of the model, an assumption was made that the implementation of preventive actions on any number of centrifugal pumps, denoted as 'n', can facilitate the opportunity to conduct inspections on the spare pump. This rate of opportunity is denoted as $n\lambda$ given as $\mu + (\frac{1}{M})$, where, M is the optimized time for preventive maintenance of the principal system. Therefore, μ and λ becomes the additional parameters for the combined (principal and spare) system. In the case study of this thesis, n is taken as 1 (see Figure 14). The rate of opportunity to inspect the spare pump is a factor dependent on the number of centrifugal pumps present in the principal system.

Both systems' cases consist of 5 decision variables (K, D, M, S, T) which were optimized together. The analytical and optimal analysis was done in Python 3.7 installed on a computer with Intel(R) Core (TM) i7-8565U, CPU @1.80GHz 1.99GHz, 7.69GB of usable RAM, 64bit operating system, and x64-based processor.

4.7 PARAMETER INFORMATION

Table 12 shows the values of each parameter for the base case

Table 12: Parameter values for base case

Parameter	Value
τ_1	1.5 years
τ_2	5 years
β_1	2
β_2	3
s	0.1
L	0.5 year
C_I	0.05 Rs
C_R	1 Rs
C_F	10 Rs
C_{UD}	100 Rs
C_O	0.3 Rs
T_R	0.003 year
T_I	0.00091 year
T_F	0.0082 year
*μ	0.125/year
**λ	0.254/year

Source: This research (2023)

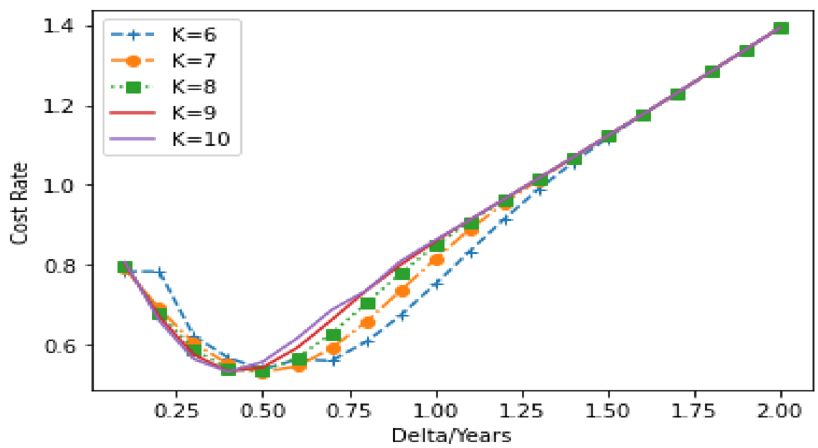
Where, * and ** are derived parameters from the KDM model.

The value of C_{UD} is the highest because it is related to the logic that a big consequence is associated with unmet demands (RODRIGUES, CAVALCANTE, ALBERTI, 2023). C_O is always less than C_R (MELO et al., 2022). Also, corrective actions are logically more expensive than other actions, hence, $C_O < C_R < C_F$ (SINISTERRA et al., 2023).

4.8 RESULT PRESENTATION

For the principal system (KDM) policy, Figures 40 and 41 show the behaviour of the long run cost rate versus D and M respectively.

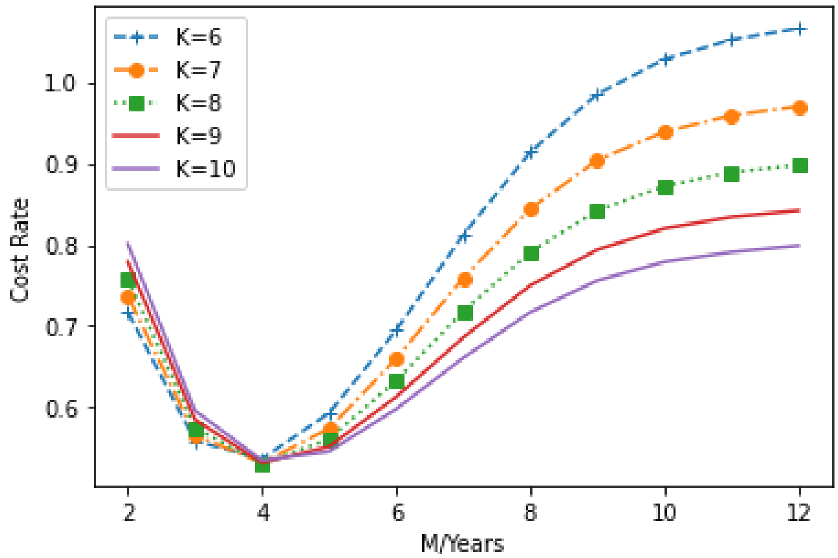
Figure 40: Cost rate Versus D



Source: This research (2023)

In fig 40 above, for each value of K (6-10), the values of D were varied between 0.2 and 2 at the optimal value for M, for instance, at K=6, M*=2.637. The parameter values follow that of table 11. Observing figure 41, the policy for the principal system suggests that at D (i.e., interval between inspections) at 0.5years (6 months), the best K is 7. For D values above 1.5 years, independently on the chosen K, the long run cost becomes expensive. Therefore, for the manager, the policy suggests performing inspections every 6 months.

Figure 41: Cost rate Versus M



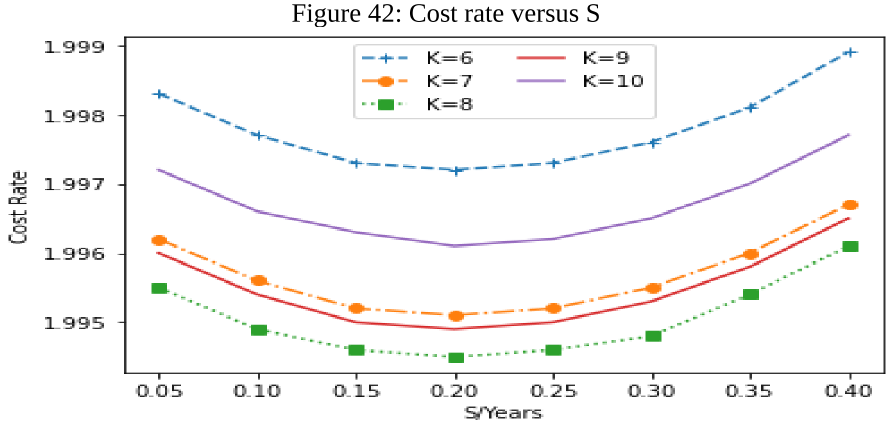
Source: This research (2023)

In fig 41 above, for each value of K (6-10), the values of M were varied between 2 and 12 at the optimal value for D, for instance, at K=6, D*=0.2996. The parameter values follow that of table 12.

Observing fig 42, the model recommends that the best time for preventive maintenance for the principal system is 4 years for any value of K. If, for any reason, the manager decides to perform preventive maintenance before 4 years, the best K is 6 (which could be seen by the doted blue line on the graph), whereas, if he decides to perform a preventive maintenance after 4 years, the best K is 10 (which could be seen by the purple line on the graph).

For the integrated system (KDMST) policy, Figures 42 and 43 shows the behaviour of the long run cost rate versus S and T respectively

Figure 42: Cost rate versus S

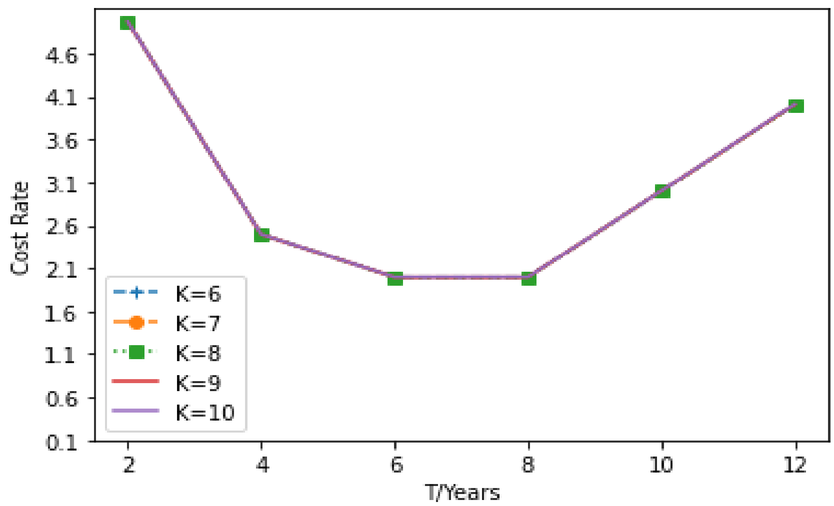


Source: This research (2023)

In fig 42 above, for each value of K (6-10), the values of S were varied between 0.05 and 0.4 at the optimal value for D, M, and T. For instance, at K=6, D*=0.5588, M*=3.717 and T*=8.0374. The parameter values follow that of table 12.

Observing fig 42, it can be seen that the best K value that gives the minimum cost rate is 8. Independently on the value of K, the optimal S is approximately 0.2 years.

Figure 43: Cost rate versus T



Source: This research (2023)

In fig 43 above, for each value of K (6-10), the values of T were varied between 2 and 12 at the optimal value for D, M, and S. For instance, at K=6, D*=0.5588, M*=3.7208 and S*=0.0676. The parameter values follow that of table 12.

The observed behavior of the K values in the figure is intriguing. It is evident that the cost rate exhibits limited sensitivity to variations in the K values. This can be attributed to the adaptive nature of D, M, and S, which collectively ensure the attainment of the lowest cost rate. However, it is noteworthy that the optimal cost rate, regardless of the K value, is consistently achieved within the time frame of 6 to 8 years. Hence, according to the integrated policy, it is advisable to schedule preventive maintenance for the spare system within this timeframe. Performing maintenance prior to this range may lead to increased cost rates irrespective of the K value, while maintenance conducted after 8 years could similarly result in elevated cost rates, irrespective of the K value.

Table 13: Simulation Results for the Integrated Policy

Case	Parameters											Variables					Cost rate	percentage change in base
	τ_1	τ_2	β_1	β_2	s	L	C_I	C_R	C_F	C_O	C_{UD}	K	D	M	S	T		
Base	1.5	5	2	3	0.1	0.5	0.05	1	10	0.3	100	8	0.4631	4.006	0.2046	8.0317	1.9945	0
1	1.5	4	2	3	0.1	0.5	0.05	1	10	0.3	100	7	0.426	3.2581	0.1741	6.7272	2.3883	19.74429682
2	1.5	6	2	3	0.1	0.5	0.05	1	10	0.3	100	9	0.4923	4.7506	0.2422	10.068	1.7044	-14.54499875
3	1.5	5	1.5	3	0.1	0.5	0.05	1	10	0.3	100	8	0.4621	3.997	0.2047	8.0453	1.9969	0.12033091
4	1.5	5	3	3	0.1	0.5	0.05	1	10	0.3	100	8	0.4634	4.009	0.2062	8.008	1.9891	-0.270744548
5	1.5	5	2	2	0.1	0.5	0.05	1	10	0.3	100	10	0.4244	4.5652	0.1857	10.8956	2.1993	10.26823765
6	1.5	5	2	4	0.1	0.5	0.05	1	10	0.3	100	6	0.571	3.7695	0.2182	7.5577	1.8666	-6.412634746
7	1.5	5	2	3	0	0.5	0.05	1	10	0.3	100	0	NA	2.9443	0.2362	7.8994	1.7526	-12.12835297
8	1.5	5	2	3	0.2	0.5	0.05	1	10	0.3	100	10	0.4005	4.2794	0.1799	8.1973	2.2387	12.24367009
9	1	5	2	3	0.1	0.5	0.05	1	10	0.3	100	8	0.4641	4.0159	0.1981	8.1687	2.0471	2.637252444
10	2.5	5	2	3	0.1	0.5	0.05	1	10	0.3	100	7	0.4993	3.8127	0.2178	7.8858	1.9078	-4.346954124
11	1.5	5	2	3	0.1	0.5	0.01	1	10	0.3	100	10	0.3662	3.9213	0.2047	8.0249	1.8939	-5.043870644
12	1.5	5	2	3	0.1	0.5	0.1	1	10	0.3	100	7	0.5614	4.3328	0.185	10.9545	2.3039	15.51265981
13	1.5	5	2	3	0.1	0.5	0.05	0.8	10	0.3	100	7	0.4848	3.7124	0.2051	8.0444	1.9354	-2.963148659
14	1.5	5	2	3	0.1	0.5	0.05	1.2	10	0.3	100	9	0.4432	4.2754	0.2048	8.0302	2.0506	2.812735021
15	1.5	5	2	3	0.1	0.5	0.05	1	8	0.3	100	7	0.5354	4.0929	0.2122	6.509	1.8607	-6.708448233
16	1.5	5	2	3	0.1	0.5	0.05	1	12	0.3	100	9	0.4092	3.9519	0.2033	11.2012	2.054	2.98320381
17	1.5	5	2	3	0.1	0.5	0.05	1	10	0.2	100	8	0.4631	4.0069	0.1405	8.0317	1.9731	-1.072950614
18	1.5	5	2	3	0.1	0.5	0.05	1	10	0.4	100	8	0.4632	4.0071	0.2413	8.0254	2.0155	1.052895463
19	1.5	5	2	3	0.1	0.5	0.05	1	10	0.3	80	8	0.4627	4.0024	0.2471	11.0121	1.7463	-12.44422161
20	1.5	5	2	3	0.1	0.5	0.05	1	10	0.3	120	8	0.4629	4.0053	0.1824	6.7011	2.1741	9.004763099
21	1.5	5	2	3	0.1	0.1	0.05	1	10	0.3	100	4	1.1235	5.2295	0.2455	10.8754	1.0211	-48.80421158
22	1.5	5	2	3	0.1	1	0.05	1	10	0.3	100	9	0.3606	3.4826	0.1675	6.609	2.4236	21.51416395

4.8.1 Discussions of Results for the integrated policy

Referring to Table 13, showing the integrated optimization, actions that increase the impact of accelerate the wear and tear of the gland seal as analyzed in case 1 by decreasing the characteristic life parameter of the strong sub-population, leads to a significant increase in costs and decreasing related to all decision variables associated to the inspection/replacement actions of the principal and spare system. On the other hand, increasing the characteristic life of the strong sub-population can have the opposite effect, resulting in a lower cost rate.

In Case 7, the zero chance of a weak item being used in the heterogeneous population suggests that no maintenance inspections are necessary. This underscores the critical role of high-quality maintenance practices. Moreover, the absence of substandard spare parts results in a marked reduction in cost rates. In case 8, the increase of a percentage of weak item in the population showed a huge number of inspections and an increased cost-rate. This shows that the time until a preventive maintenance could be delayed.

The optimal policy and cost rate are significantly affected by the variability of several costs, as evidenced by Cases 11-20. Notably, Cases 11-20 reflect an increase in cost parameters that may arise from outsourcing maintenance personnel. To mitigate these costs, assigning inspections to the operations team aligns with the autonomous maintenance principle of Total Productive Maintenance (TPM). Additionally, enhancing defect visibility for operators would expedite and reduce the cost of maintenance actions.

In cases 11 and 12, when it is cheaper to do inspections (case 11), the model recommends more inspections. In contrast, in Case 12, the cost of inspection exceeds the base case cost, resulting in a reduced recommendation for inspections.

For cases 13 and 14, In Case 14, where the cost of replacement is higher, the model suggests for the principal system, performing preventive maintenance later (M=4.27). On the other hand, in Case 13, where the cost of replacement is lower, the model recommends earlier (M=3.71) preventive maintenance.

In cases 15 and 16, the model predicts different inspection frequencies and preventive replacement timing depending on the cost of failure. Specifically, in Case 16, where the cost of failure is higher, the model recommends more frequent inspections compared to the base case. Conversely, in Case 15, where the cost of failure is lower, the model suggests performing fewer inspections. Additionally, the model recommends earlier preventive replacement timing in situations where the cost of failure is bigger (M=3.95).

For cases 17 and 18, when the cost of opportunity is cheaper, (case 17), the model recommends a wider window of opportunity, but when the cost of opportunity is more expensive (case 18), it recommends a shorter window of opportunity than the base case. Hence, the length of the window of opportunity is indirectly proportional to the cost of opportunity.

For cases 19 and 20, when the cost of unmet demand is cheaper, the model predicts a shorter window of opportunity, but when the cost of unmet demand is more expensive (case 20), it predicts a wider window of opportunity.

Case 22 serves to illustrate the effect of increasing the mean (L) of the exponential distribution of delay time, which results in a decrease in delay time (1/L). The study found that as the time spent in the defective state decreases, an increase in the frequency of inspections is required to detect defects earlier. This observation is also evident in the work of Sinisterra et al. (2023) where, when the mean sojourn of the machine in the defective state is shorter, their model suggested an increase in the frequency of inspection.

4.9 FINAL REMARKS ON THE CHAPTER

An integrated opportunistic maintenance policy was developed for a principal and standby system of centrifugal pumps used in the mining industry. The KDM policy was adopted for the principal system. An ST model was developed for the spare system. The MTBOF result from the principal system for the gland seal component was used to calculate the additional parameters (μ and λ) for the ST model. Results from the KDM policy were observed. Both models (KDM and ST) were then combined as a KDMST integrated policy which was optimized with the objectives of determining the optimal number of inspections, inspection intervals, window of opportunity, and optimal times for preventive maintenance of the primary and standby system. A numerical case study of the policy on centrifugal pumps was analyzed by investigating its behavior for various parameter values such as the characteristic life and shape for both strong and weak spares following a Weibull distribution, inspection costs, preventive and failure replacement costs, opportunity costs, and unmet demand costs. The proposed policy suggests increasing the window of opportunity for inspecting the spare system when the cost of unmet demand is high. This recommendation is based on the premise that conducting more inspections is less expensive than facing unmet demand and also by performing more inspections, the manager can ascertain that the spare system is always readily available to perform its intended function. Similarly, when the cost of opportunity decreases, the policy suggests increasing the window of opportunity for inspection. This framework can be applied to industries with similar equipment in similar environments. Future studies could focus on exploring the relationship between the window of opportunity and the optimal cost rate for different types of pumps under varying operating conditions.

5 CONCLUSIONS OF THE THESIS

The primary objective of this thesis is to discuss some contributions of maintenance policies for centrifugal pump in an iron ore concentrate process plant. To achieve this goal, the author developed two models. The equipment of interest for this study is the centrifugal pump utilized in the production of iron ore concentrates in a Nigerian mining industry. The reason for selecting this particular equipment is that the author has significant industrial experience working in this industry and has identified several issues caused by sub-optimal maintenance policies. These sub-optimal policies are often attributed to inadequate maintenance data, poorly timed maintenance schedules, or a failure to utilize optimal opportunities for maintenance, resulting in substandard product quality. Thus, it is crucial to propose maintenance policies that can address these issues. In this thesis, we propose two model frameworks to achieve this aim.

The first study proposed a reinforcement learning approach for condition-based maintenance of centrifugal pumps used in the production of iron ore concentrates. A variance gamma process degradation model is developed to simulate the degradation process of the pump, and actions are recommended based on performance features to minimize long-term maintenance costs. This solved the first problem of deciding the actions to take to avoid an outright failure of the pump. The approach outperforms a corrective maintenance policy and is effective in predicting lower maintenance costs and fewer stoppages for slower degrading pumps.

The second study developed an integrated opportunistic maintenance policy for a cold-standby system consisting of a principal set of pumps and a standby set that is activated in the event of failure. The principle of the model developed is based on the delay-time concept. One maintenance (KDM) policy was adopted. The other (ST) policy was developed. The two policies were integrated as a (KDMST) policy. The separate and combined optimization are defined. This solved the second general problem of determining the optimal number of inspections, opportunity window and time for preventive replacement for the principal and spare pump. Simulation and sensitivity analysis show a strong correlation with existing studies, and the proposed policy can be readily applied to other industries that utilize similar equipment.

In summary, this thesis has discussed the contributions of maintenance policies for centrifugal pumps, demonstrating that the reinforcement learning approach for condition-based maintenance and the integrated opportunistic maintenance policy for a cold standby system offer effective solutions for minimizing long-term maintenance costs

5.1 LIMITATIONS AND FUTURE LINES OF RESEARCH

The limitations of the study are

1. The study area for the models is restricted to an Iron ore company based in Nigeria
2. The simple case of the second model could be expanded to include more centrifugal pumps involved in the spare system.

The works presented in the studies above suggest several avenues for future research. Here are some potential directions:

1 Expanding the physical model of the centrifugal pump: Further development of the physical model can be conducted to generate additional feature data for machine-learning algorithms. This can include incorporating more degradation factors or analyzing the effects of different types of faults on the pump's performance.

2 Enhancing the reinforcement learning approach: The reinforcement learning approach proposed in the first study can be further enhanced by applying the approach to more sophisticated environment such as, in complex equipment arrangement where there is a dependency of the pumps on one another.

3 Developing optimal opportunistic maintenance policies for different types of systems: The second study provides a framework for developing optimal opportunistic maintenance policies for cold-standby systems. Future research can apply this concept to other types of systems, such as hot-standby or warm-standby systems. The effectiveness of the policies can be compared to other maintenance strategies, and the impact of different system parameters can be evaluated.

4 Applying the proposed approaches to other industries: The studies above focus on the mining industry and the centrifugal pump, but the proposed approaches can be applied to other industries and equipment types. Future research can investigate the feasibility and effectiveness of applying these approaches to different industries, such as the oil and gas industry, and different types of equipment, such as turbines or compressors.

5 Evaluating the economic impact of the proposed maintenance policies: While the studies above focus on improving maintenance strategies that reduce maintenance costs, the economic

impact of these policies on the overall profitability of the organization should also be evaluated. Future research can assess the impact of the proposed policies on the organization's revenue, profitability, and return on investment.

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APPENDIX A - PSEUDOCODE FOR THE DQN MACHINE

1 Import necessary libraries
2 Initialize replay memory D to size N
3 Input hyperparameters: state size S_s , action size A_s , gamma γ , target steps T_s , Batch size B_s epsilon ϵ , epsilon decay ϵ_σ , learning rate L_r , epsilon minimum ϵ_m .
4 Build neural network model:
5 Initialize the neural network with random weights
6 **For** each iteration=1 to j, do:
7 Initialize S_t as starting state
8 Generate random numbers (randN)
9 If randN $\leq \epsilon$
10 Select action a_t via exploration
11 Else: exploit
12 Execute a_t in emulator and observe R_{t+1} and S_{t+1}
13 Store experience $e[S_t, a_t, R_{t+1}, S_{t+1}]$ as experience relay e
14 Sample random batch from e memory
15 **For** $S_t, a_t, R_{t+1}, S_{t+1}$ in batch,
16 Pass batch of preprocessed states to policy network
17 Calculate loss by comparing the Q-value output from the network in e and the corresponding target Q-value of the same action according to:
18 $E[R_{t+1} + \gamma \max_{a'} q_\pi(s', a')] - E[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}] = loss$
19 Update weight in neural network with gradient descent to minimize loss
20 Do until $\epsilon = \epsilon_m$
21 **End**
22 **End iteration**
23 Save model

APPENDIX B - PSEUDOCODE FOR THE MAINTENANCE ENVIRONMENT

1 Import necessary libraries
2 Input state variable parameters: minimum value for vibration = V_m , and $V_\theta, V_v, V_\mu, V_\sigma$
Minimum value for temperature = T_m, and $T_\theta, T_v, T_\mu, T_\sigma$
Minimum value for pressure = P_m, and $P_\theta, P_v, P_\mu, P_\sigma$
3 Input repair cost C_r , maintenance cost C_m, failure cost C_f, electricity consumption cost C_e, penalty cost C_p
4 Initialize actual time, running time, reward
5 Initialize state of pump:
    0 = operational, 1= degrading, 2= failed
    Generate the difference of two gamma processes parameters η_p and η_n:

$$\eta_p = \frac{\theta v}{2} + \sqrt{\frac{\theta^2 v^2}{4} + \frac{\sigma^2 v}{2}} \qquad \eta_n = -\frac{\theta v}{2} + \sqrt{\frac{\theta^2 v^2}{4} + \frac{\sigma^2 v}{2}}$$

6 Degrade pump according to variance gamma process:
7 **For** $t < t_N$ ($t_N =$ maximum simulation time)
8 Generate Random gamma number ($rand\Gamma$)
9 Vibration transition = $V_m + [rand\Gamma\left(\frac{t}{V_v}, \eta_p\right)] - [rand\Gamma\left(\frac{t}{V_v}, \eta_n\right)]$
10 Classify vibration transition to states of pumps, 0, 1, 2
11 Pressure transition = $P_m + [rand\Gamma\left(\frac{t}{P_v}, \eta_p\right)] - [rand\Gamma\left(\frac{t}{P_v}, \eta_n\right)]$
12 Classify pressure transition to states of pumps, 0, 1, 2
13 Temperature transition=$T_m + [rand\Gamma\left(\frac{t}{T_v}, \eta_p\right)] - [rand\Gamma\left(\frac{t}{T_v}, \eta_n\right)]$
14 Classify temperature transition to states of pumps, 0, 1, 2
15 End
16 Action selection rules:
17 If action selected = 0 and pump is in operational state:
18 Add the electricity consumption cost C_e
19 If action selected = 0, but pump is degrading:
20 $C_{em} = [0.0144e^{0.2677V_t}]$
21 Elseif action selected = 0 and the pump is not operational:
22 Add penalty cost C_p for wrong decision
23 End
24 If action selected = 1 but pump is operational and not degrading:
25 Add repair cost C_r : pump is already stopped
26 Penalize the agent for wrong decision with C_p
27 Elseif action selected = 1 but pump is operational and degrading:
28 Add maintenance cost C_m
29 Else:
30 Add the failure cost C_f
31 End
32 Create brain
33 Train agent
34 End