MAINTENANCE SIMULATION OF A CHEMICAL PLANT IN CAMEROON

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OCTOBER, 2023

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IŞIK UNIVERSITY, School of Graduate Studies, Industrial Engineering Master Program,
2023

This thesis has been submitted IŞIK UNIVERSITY School of Graduate Studies for a Master's Degree

IŞIK UNIVERSITY
OCTOBER, 2023

IŞIK UNIVERSITY

SCHOOL OF GRADUATE STUDIES

INDUSTRIAL ENGINEERING MASTER PROGRAM

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APPROVAL DATE: 30/10/2023

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ABSTRACT

In the field of manufacturing, remarkable strides have been made in the development of predictive maintenance strategies. The research has incorporated cutting-edge technological innovations, such as machine learning, artificial intelligence, and the Internet of Things (IoT). Manufacturers can now proactively identify and address equipment malfunctions. This research study employs a degradation model simulation to evaluate and predict the remaining lifespan of a rotating element bearing in the manufacturing assembly line of a chemical plant situated in Cameroon. Additionally, the objective of this study is to perform a comparative analysis that seeks to assess the impact of implementing preventive and predictive maintenance strategies on the overall operational efficiency of a manufacturing system characterized by a series-parallel configuration. The study reveals that the predictive maintenance policy is more significant in manufacturing system where addressing system throughput or implementation cost. This highlights the enhanced efficiency and cost-effectiveness associated with predictive maintenance in manufacturing operations.

Keywords: Predictive Maintenance, Degradation Model, Remaining Useful Life, Simulation.

KAMERUN'DAKİ BİR PESTİSİT ÜRETİM TESİSİ İÇİN ÖNGÖRÜSÜ BAKIM SİMÜLASYONU

ÖZET

Üretim alanında, kestirimci bakım stratejilerinin geliştirilmesinde dikkate değer ilerlemeler kaydedilmiştir. Araştırma, makine öğrenimi, yapay zeka ve Nesnelerin İnterneti (IoT) gibi en ileri teknolojik yenilikleri içeriyor. Üreticiler artık ekipman arızalarını proaktif olarak tespit edip giderebiliyor. Bu araştırma çalışması, Kamerun'da bulunan bir kimya fabrikasının imalat montaj hattındaki döner elemanlı rulmanın kalan ömrünü değerlendirmek ve tahmin etmek için bir bozulma modeli simülasyonu kullanmaktadır. Ek olarak bu çalışmanın amacı, önleyici ve kestirimci bakım stratejilerinin uygulanmasının, seri-paralel konfigürasyonla karakterize edilen bir üretim sisteminin genel operasyonel verimliliği üzerindeki etkisini değerlendirmeyi amaçlayan karşılaştırmalı bir analiz gerçekleştirmektir. Çalışma, sistem verimi veya uygulama maliyetinin ele alındığı üretim sisteminde kestirimci bakım politikasının daha önemli olduğunu ortaya koyuyor. Bu, üretim operasyonlarında kestirimci bakımla ilişkili gelişmiş verimliliği ve maliyet etkinliğini vurgulamaktadır.

Anahtar Kelimeler: Kestirimci Bakım, Bozunma Modeli, Kalan Faydalı Ömür, Simülasyon.

ACKNOWLEDGEMENT

My years at graduate school will remain one of the best experiences in my life, as they have exposed me to a wealth of knowledge and opportunities in my career. However, I recognize that this journey would not have been possible without the invaluable support of several individuals and institutions. First and foremost, I wish to extend my utmost appreciation to the administration of IŞIK UNIVERSITY for bestowing upon me the privilege to embark upon my Master's program within their esteemed academic establishment. The aforementioned experience has proven to be truly transformative, instilling within me deep appreciation for the opportunity afforded to me. I would also like to express my sincere gratitude to Dr. SONYA JAVADI, my supervisor and professor. It has been an immense privilege to work alongside you, not only in the context of my thesis but also throughout my coursework. I am honored to have had the chance to learn from your vast knowledge and skills during the course of my studies. I am also grateful to the Industrial Engineering Department and all my professors who have played a significant role in guiding me on this educational journey. Your support and guidance have been instrumental in my academic growth. To my fellow graduate student colleagues, I want to express my appreciation for your help and mentorship throughout my program. I would like to take a moment to convey my deepest gratitude to my beloved parents, Mr. and Mrs. SIMON NJI, as well as my dear brother and best friend, NJICHIFU ERNEST. Your unwavering love and care have been my pillars of strength throughout this journey. Finally, I must acknowledge the unwavering support of my husband, ALBERT MARLON SESSAY.

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ABBREVIATION LIST

CNN	Convolutional Neural Network
FFT	Fast Fourier Transform
FMS	Flexible Manufacturing Systems
FMEA	Failure Mode and Effects Analysis
CEMAC	Economic Community of Central African States
CBM	Condition-Based Maintenance
FCFA	Franc of the Communauté Financière Africaine
FNN	Feedforward Neural Network
Holfarcam	Holland Farming Cameroon
LSTM	Long-short-term Memory
MSCNN	Multi-scale Convolutional Neutral Network
PCA	Principal Component Analysis
PM	Preventive Maintenance
PdM	Predictive Maintenance
PHM	Prognostics and Health Management
RBI	Risk Based Inspection
RCM	Reliability Centered Maintenance
RUL	Remaining Useful Life
Sarl	Limited Liability Company
SL	Solution Concentrate
TPM	Total Productive Maintenance

CHAPTER 1

1. INTRODUCTION

In earlier times, many companies perceived their maintenance departments as having little or no impact on the company's profitability. However, as industries have evolved, the perspective has undergone a transformation. This shift is driven by the recognition that any competent plant manager would seek to achieve significant cost savings, consequently, it becomes evident that companies with effective maintenance management can indeed realize substantial cost savings.

(Swanson, 1999) Currently, maintenance is widely recognized as the most significant element within the production process, exerting substantial influence on product quality, plant uptime, and the capacity to adhere to delivery timelines. (Alguindigue, Loskiewicz-Buczak, & Uhrig, 1993). This perspective is particularly emphasized in the manufacturing sector, where a noticeable trend has emerged, aiming to challenge contemporary lean and just-in-time manufacturing concepts. The reliance on minimal buffers and inventory within this manufacturing system presents a notable limitation, as it intensifies various impact of unforeseen disruptions that may occur throughout the manufacturing process. The failure of equipment in such a system is exceedingly costly, as it results in automatic production stoppages, delayed shipping schedules, and, consequently, diminished customer satisfaction.

This study endeavors to employ simulation methods in order to examine the effects of various maintenance strategies on the overall importance of a particular system. Most production systems encompass complex operations and processes in industrial settings that enable the production of goods. In this study, we introduce several predictive maintenance policies and evaluate their effectiveness by analyzing system performance indicators, specifically throughput and equipment utilization.

The objective of predictive maintenance is to ascertain or anticipate the probable occurrence of system failure or component deterioration through the application of diverse approaches including empirical knowledge, fundamental principles, or machine learning methodologies. By identifying and replacing faulty components before they break down, predictive maintenance aims to minimize system downtime (Voronov, Kazansky, & Davydov, 2020). Monitoring the health of machines has gained significant attention in the manufacturing and maintenance industry, as unplanned downtime can have severe consequences, including production interruptions and costly repairs for companies. For instance, components like rotating element bearings and gear reducers have been identified as commonly used parts in rotating machinery, such as chemical reactors, making failures in these components a natural occurrence.

In today's modern economy, large systems like manufacturing facilities, transportation networks, and health monitoring systems are built with highly interconnected components. This interconnectedness necessitates frequent observations to support various critical decision-making processes (Licht & Deshmukh, 2002). The advancement of wireless technology and electronics has had a significant impact on the sensory observations of these systems (Akyildiz, Su, Sankara., Subramaniam, & Cayirci, 2002).

1.1 Maintenance Management

Technological advancements and efficiency improvements are continuously driving companies to find ways to streamline operations, cut costs, and enhance product quality in their quest to stay competitive. One significant area of focus is automation. Manufacturing processes that were previously executed manually are now being replaced by machines, robots, and computer-controlled systems. This not only accelerates production but also diminishes the likelihood of errors and defects.

Furthermore, the utilization of data analytics and artificial intelligence is on the rise. Manufacturers are gathering and analyzing vast amounts of data to gain insights into their processes and make data-driven decisions. This enables them to pinpoint areas for improvement, optimize inventory levels, and predict and prevent equipment failures. Challenges often arise in the long run due to unscheduled maintenance activities. The choice of a maintenance strategy depends on factors such as equipment criticality, cost considerations, available resources. Selecting appropriate maintenance approach for a specific system, organizations can effectively manage their assets, reduce downtime, and optimize operational efficiency. In subsequent paragraphs, this study explore the various categories of maintenance strategies. It will provide an outline of each strategy, followed by a detailed discussion on their key characteristics, benefits, and limitations.

1.1.1 Corrective Maintenance

This strategy is successfully perform by highly skilled technicians and a well-stocked machinery spare parts warehouse are required (Stephens, 2010). While reactive maintenance may be beneficial and cost-effective for newly installed machinery, it becomes more challenging as machinery ages. Sudden failures, such as a bearing failure, can lead to downtime, resulting in the shutdown of the entire manufacturing line. Furthermore, sudden failures of rotating machines, like bearings, can pose industrial accidents and fatalities, further increasing maintenance costs. Initially, the adoption of reactive maintenance may seem attractive due to its simplicity and economic feasibility.

However, it has the potential to cause prolonged periods of inactivity, safety hazards, and substantial expenses over time. It is recommended to employ a combination of reactive and other maintenance techniques for bearings, considering the criticality and safety implications of the equipment, to determine the optimal frequency and scope of interventions. For example, **Figure 1.1** is a schematic representation of corrective/reactive maintenance.

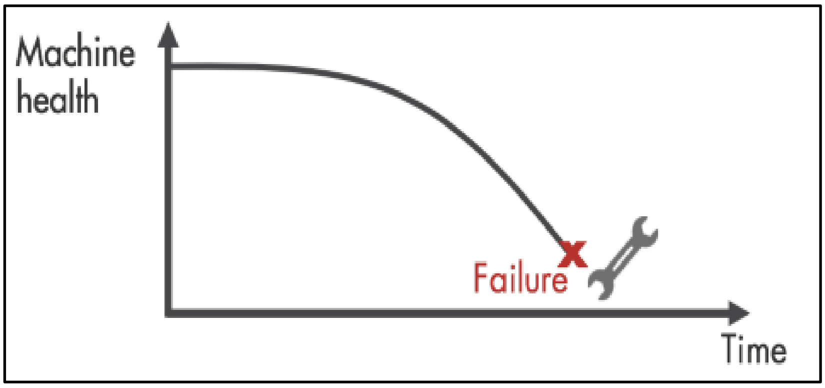

Figure 1. 1 Reactive Maintenance Illustration

Source: Schalk, T. (2019). *Introduction to Predictive Maintenance with MATLAB.*

1.1.2 Preventive Maintenance

This strategy is adopted across various sectors, with its primary focus on scheduling regular services and repairs for machine parts to detect and address issues before they escalate (Kaiser K. , 2007). By proactively preventing equipment failure and maintaining optimal working conditions, this strategy aims at extending the lifespan of machinery while simultaneously improving its reliability, performance, and operational safety. This approach also plays a crucial role in identifying and addressing potential safety concerns associated with worn-out bearing components.

However, in the short term, preventive maintenance may result in higher costs as it involves planned maintenance work that may or may not be immediately necessary. There is also a risk of over-maintenance, where components are replaced prematurely before wearing out. Additionally, preventive maintenance can be time-consuming due to routine inspections and equipment maintenance, potentially optimal bearing performance and minimize unexpected failures, it is advisable to incorporate preventive maintenance in conjunction with other maintenance measures. Affecting productivity.

For example, implementing a preventive maintenance strategy is crucial for ensuring optimal bearing functionality and longevity. This typically involves cleaning, lubrication, inspection, alignment checks, and vibration analysis, as recommended by the manufacturer. The frequency and timing of these procedures may vary depending on equipment usage and importance. To achieve **Figure 1.2** is the schematic representation of this strategy.

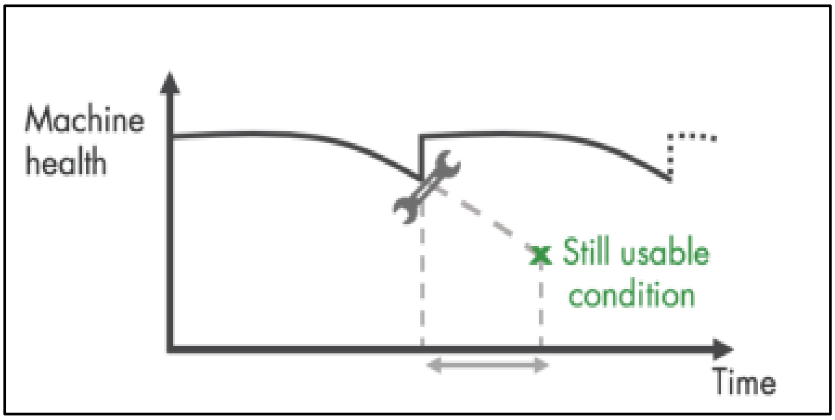

Figure 1. 2 Illustration of Preventive Maintenance

Source: Schalk, T. (2019). *Introduction to Predictive Maintenance with MATLAB.*

1.1.3 Predictive Maintenance

Practicing predictive maintenance (PdM) involves the use of data analytics techniques to predict the probability of equipment malfunction before it occurs. By applying preventive maintenance measures based on these predictions, potential accidents can be prevented, resulting in significant cost and time savings. PdM can be implemented through various strategies, primarily involving the collection of relevant sensory data from machinery and the use of this data to build prognostic models that forecast the likelihood of equipment malfunction. Once a model is developed, it can be used for maintenance planning and timely notification of potential issues to maintenance personnel.

PdM combines the advantages of both reactive and preventive maintenance while minimizing their drawbacks. It determines the optimal timing for predicting equipment failure, ensuring that maintenance activities are performed only when necessary. Implementing this strategy can lead to benefits in terms of time management, cost efficiency, and accident prevention (Stephens, 2010). **Figure 1.3** illustrates the scheduled predictive maintenance process.

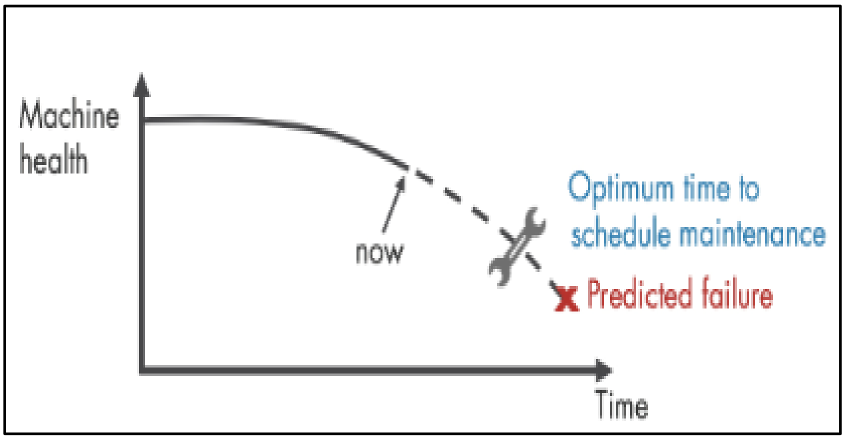

Figure 1. 3 Predictive Maintenance Illustration

Source: Schalk, T. (2019). *Introduction to Predictive Maintenance with MATLAB.*

1.2 Degradation Modelling

The aforementioned mathematical framework serves as a tool for representing the progressive development of deteriorated signals acquired through condition monitoring methodologies, because degradation processes often exhibit a stochastic or random nature, similar components tend to show different rates of degradation. (Lu, Meeker, & Escobar, 1996). Suggested a deterioration study incising that the level of deterioration is directly proportional to the operational time, with a random deterioration rate. The authors employed random coefficient growth models to simulate the trajectory of the deterioration signal.

The deterioration mathematical model was further separated into major categories: linear degradation and exponential degradation. Linear degradation models prove to be advantageous in cases where the monitored signal is on a logarithmic scale or when the component under observation does not undergo cumulative degradation. These devices are commonly utilized in situations where the stochastic parameters related to the deterioration of the system are not known and there is no prior data available on the degradation of the system components (Yu, Cao, & Schniederjans, 2017).A graphical representation of a linear degradation path of a mechanical component is shown in **Figure 1.4**

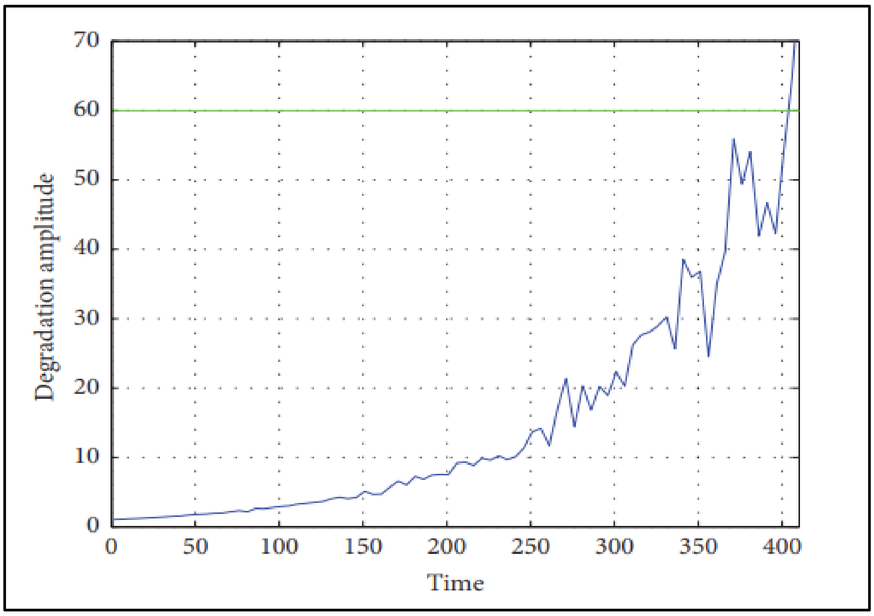

Figure 1. 4 Linear Degradation Simulation

Source: Yu, Y., Cao, R. Q., & Schniederjans, D. (2017). Cloud computing and its impact on service level a multi-agent simulation model. *International Journal of Production Research*, *55(15)*, 4341-4353.

On the other hand, exponential Degradation modeling is when degradation is directly proportional to the current condition of the system. This specific degradation model holds particular significance in our study since it possess known bearing degradation data, which is indicative of cumulative degradation. **Figure 1.5** provides a visual representation of an exponential degradation trend for a mechanical component.

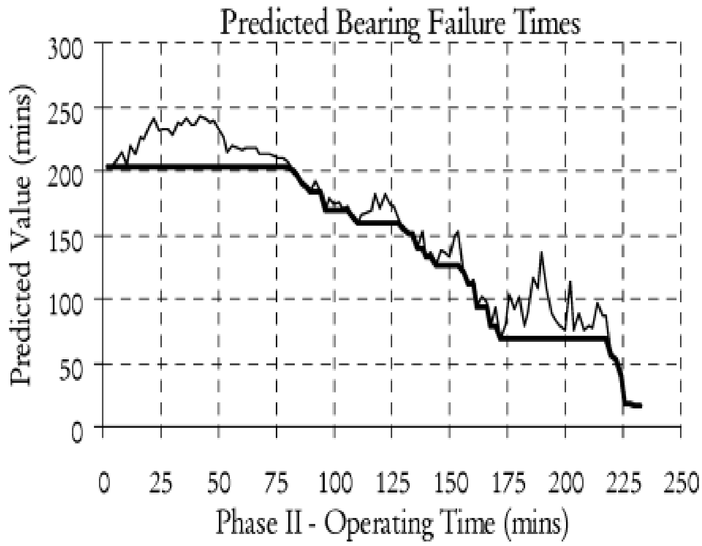

Figure 1. 5 Exponential Degradation Model.
Source: Gebraeel, N. (2006). Sensory-Updated Residual Life Distributions for Components With Exponential Degradation Patterns. *IEEE Transactions on Automation Science and Engineering, 4(3)*, 382-393.

The author introduced a parametric degradation model that uses real-time sensory data from online condition monitoring to determine the distribution of residual life. This proposed model adequately encapsulates the functional expression that characterizes the degradation signals of a component within a particular population. Throughout various studies and research endeavors, the author's theory on deterioration has been thoroughly scrutinized, as it has been found to profoundly shape decision-making processes concerning maintenance management and the formulation of replacement strategies.

1.3 Research Objective

The objective of this research is as follows;

1. Determination of the RUL of rolling bearing element.

2. The present study aims to compare the impact of preventive maintenance and predictive maintenance policies on the performance of the manufacturing system, particularly under varying reliability levels.

1.4 HOLFARCAM Company

The HOLFARCAM Sarl facility is located in Cameroon's Littoral region. HOLFARCAM is one of the 14 largest producers and importers of fertilizers and plant protection products in the country, contributing to over 20% of the nation's agrochemical imports. Established in 2006, HOLFARCAM Sarl specializes in the importation and distribution of agricultural inputs, which include pesticides (herbicides, fungicides, and insecticides), fertilizers, agricultural equipment, and seeds. The company operates both within Cameroon and the CEMAC sub-region. Furthermore, the factory comprises three main production lines, which are;

- Powder Production line to produce wet powder (WP), dry flow soluble,
- Soluble Liquid Line to produce Solution Concentrate (SL),
- Liquid solution concentrate line (case study).

CHAPTER 2

2. LITERATURE REVIEW

2.1 Review on Maintenance

It exhibits plays a critical role in ensuring the reliability and longevity of machinery in industrial enterprises. Numerous empirical studies have explored various aspects of maintenance and its significant impact on organizational performance. For example (Salawu, et al., 2023) discussed the importance of maintenance management in engineering factories, highlighting the need to optimize maintenance practices to reduce downtime and improve operational efficiency. (Teixeira, Lopes, & Pires, 2023) Conducted a comprehensive examination of different maintenance strategies, including corrective, preventive, and predictive maintenance, providing a comparative analysis of their associated costs and benefits.

The maintenance process consists of multiple phases, which can be effectively analyzed using various tools and techniques. Root cause analysis is used to determine the underlying reasons behind equipment failures. Conversely, Failure Mode and Effects Analysis (FMEA) facilitates the identification of prospective failures and their subsequent ramifications. Reliability-Centered Maintenance (RCM) is a systematic approach employed to augment equipment reliability through comprehensive analysis of failure modes and strategic optimization of maintenance practices.

2.2 Simulation Analysis

Many studies have demonstrated that simulation can effectively be employed to assess the functionality of maintenance management systems, particularly in the context of maintenance policies and the manufacturing industry. (Alguindigue, Loskiewicz-Buczak, & Uhrig, 1993). For instance, a simulation modeling study was conducted to evaluate the efficacy of the significance of cellular and functional work cell layouts, taking equipment failure into account. This study considered two critical factors: The average value of work-in-process inventory and the average duration required for completing a single cycle of production. While making comparisons between preventive and reactive maintenance (Logendran & Talkington, 1997). In this study, the authors assumed that equipment conditions were monitored at equidistant time intervals, and there was a probability of equipment failure during these inspection intervals, with this probability of failure being exponential.

In another study by (Sloan & Shanthikumar, 2000). It was highlighted that successfully implementing predefined maintenance policies does not guarantee the achievement of other manufacturing strategy goals, such as improving quality and increasing flexibility. Flexible Manufacturing Systems (FMS) can be viewed as technological implementations that simultaneously enhance quality and increase flexibility. Many of the manufacturing policy objectives tend to rely on technological implementations (Ostadi & Rezaie, 2007).

2.3 Condition-based Maintenance

This maintenance strategy is widely recognized for its significant reliance on systematic monitoring of equipment condition in predicting the optimal timing for maintenance actions. Organizations can derive various advantages from this approach, including economic gains through cost reduction, enhanced dependability, and minimized instances of operational interruption. First and foremost, the application of Condition-Based Maintenance (CBM) possesses the capacity to engender cost efficiencies through the mitigation of maintenance activities' frequency. Unlike adhering to predetermined time frames for maintenance, CBM takes a more proactive approach by scheduling maintenance activities based on real-time assessments of the equipment's operational condition. This means that maintenance procedures are only executed when deemed essential, thus reducing expenses associated with unnecessary maintenance activities.

Furthermore, another significant advantage of utilizing Condition-Based Maintenance (CBM) is its potential to enhance equipment dependability through early identification of possible failures. Early detection empowers operators to promptly implement preventive measures, thereby mitigating the occurrence of equipment breakdowns. Implementing a proactive approach has the potential to prevent equipment failures and increase equipment uptime, subsequently fostering enhanced operational efficiency and productivity.

Thirdly, Condition-Based Maintenance (CBM) has the capacity to minimize operational interruptions by proactively detecting and addressing evolving issues before they manifest as equipment failures. This entails the proactive maintenance of equipment to prevent failure, resulting in a reduction in the duration required for repairs and mitigating disruptions to production schedules.

Additionally, the utilization of CBM (Condition-based Maintenance) is effectively employed to optimize and improve maintenance practices by strategically planning maintenance activities during periods of reduced demand or mitigating the adverse effects of maintenance on production schedules. Aligning maintenance activities with the organization's objectives and requirements allows for the optimal utilization of the benefits provided by Condition-Based Maintenance (CBM) while simultaneously minimizing disruptions to production processes.

2.4 Predictive Maintenance

Predictive maintenance (PdM) is a well-established maintenance methodology that employs proactive measures to anticipate possibilities of equipment failure by analyzing data from various sensors and sources. This method offers several advantages compared to traditional time-based maintenance, including improved operational efficiency, reduced downtime, and cost savings. PHM employs technology; machine learning algorithms, sensor systems and data analysis to monitor equipment in real-time. By analyzing collected data, predictive maintenance (PdM) can detect patterns indicating potential equipment failure, allowing for the prediction of necessary maintenance actions. This proactive approach reduces downtime and extends equipment lifespan.

Numerous studies have highlighted the benefits of Predictive Maintenance (PdM), including economic savings, increased reliability, and enhanced effectiveness. For example, research showed a 25% reduction in maintenance expenses and a 20% improvement in equipment uptime after implementing PdM in a manufacturing facility. Similarly, a study by (Bejaoui, Bruneo, & Xibilia, 2021) found that PdM led to a significant reduction of maintenance costs (up to 40%) and improved equipment reliability (up to 60%). Moreover, the implementation of Predictive Maintenance (PdM) can enhance safety measures by identifying and anticipating potential equipment failures before they occur, effectively reducing the risk of injuries or accidents. This intervention also has the potential to minimize environmental impact by reducing the need for oil changes and decreasing other forms of maintenance-related waste.

One of the most challenging aspect of PdM is acquiring the necessary data to develop prediction models. Ensuring the accuracy and reliability of the data can be a complex and time-consuming process. Additionally, the implementation cost of PdM poses a significant challenge, with expenses related to sensors, data analytics software, and maintenance personnel being substantial. However, despite these challenges, the costs associated with implementing a PdM program can be justified by the benefits of improved production efficiency, reduced maintenance expenses, and enhanced overall safety.

There are certain drawbacks associated with PdM, especially during the initial financial investment phase. Safeguarding the investment in the short term can be a present significant challenge, despite the numerous long-term benefits it offers. Acquiring the necessary data often entails the installation of sensors and the integration of existing data sources, which requires a deep understanding of the specific domain and comprehensive strategic planning. Establishing and configuring the communication architecture are essential prerequisites for effectively yielding results through PdM. Once the initial phase of data acquisition is complete, it becomes feasible to develop models that enable the implementation of condition monitoring and prognostic maintenance.

The effectiveness of PdM is primary dependent on the acquisition of precise and reliable data, which is sourced from a diverse range of channels, although it predominantly relies on two principal types of sensors: internal and external. One advantageous attribute of built-in sensors is their optimal positioning, which enables them to efficiently collect the necessary data.

However, a potential limitation is the prerequisite purchase of pre-installed sensors for the equipment, which typically entails a higher initial investment and may not be applicable to pre-existing machinery. Conversely, external sensors present the advantage of being deployable in diverse locations and possessing straightforward accessibility. Achieving a balance between these two aspects is indispensable, as the positioning of external sensors may be less optimal than built-in sensors. This balance ensures effective data collection for predictive maintenance.

Given the critical role that bearings play in equipment and their presence in many rotating machineries, their failure often leads to significant malfunctions. Common causes of bearing failure include overloading, over speeding, and inadequate lubrication, as identified by (Phalle & Patil, 2021). However, failure instances can also result from other factors such as corrosion and misalignment. The monitoring of bearings has traditionally relied on vibration analysis, which has been validated through several empirical studies. However, there are novel alternatives to vibration analysis, such as heat sensors and sound sensors that offer promising avenues for further exploration.

One significant constraint associated with heat sensors is the potential for delayed detection of elevated heat levels originating from the bearing. This delay may result in irreversible damage to the system's functionality before corrective measures can be implemented. Sound analysis, although a relatively recent technique, has demonstrated efficacy in various instances. However, a potential limitation of its implementation is the challenge of separating the sound signal from machine and environmental noise.

2.4.1 Degradation Models

This model is a research area that centers on the utilization of degradation signals, which are obtained through condition monitoring techniques, to capture the progressive deterioration of a component throughout its operational lifespan. These are models which offer a means to estimate the residual life distribution of the monitored component (Kaiser K. , 2007). A dual-phase approach was devised to accurately simulate the trajectory of condition-based deterioration signals across various growth model parameters. The examination of degradation models entails the utilization of data derived from degradation signals for the purpose of forecasting the remaining useful life, which is distributed across the sample population's components. (Lu & Meeker, 1993).

(Gebraeel, Lawley, Li, & Ryan, 2005) This study presents a novel approach for estimating the remaining operational lifespan of a rolling element thrust bearing utilizing a degradation signal obtained from vibration analysis. The author provided empirical evidence demonstrating that as a bearing comes to the end of its operational life, small fractures arise within the material comprising its raceway. When fissures propagate through the exterior of the raceway material, a fragment of the substance becomes dislodged. Hence, the rolling surface of the bearing undergoes the occurrence of discontinuities, commonly referred to as spalls. The generation of spalls is a common occurrence in numerous bearing malfunction mechanisms, resulting in the manifestation of distinct vibration frequencies. The occurrence of these flawed frequencies is contingent on the bearing configuration, encompassing factors such as the quantity of rolling elements, the peculiarities of its geometry, and also the rotational velocity at which it operates.

The author's analysis reveals that at approximately 30% of the bearing's operational lifespan, there is an absence of substantial alterations in the vibration spectrum. However, when reaching the 40% threshold, certain frequencies begin to manifest, exhibiting a progressive increase in their respective amplitudes as time progresses. The properties extracted from each vibration spectrum, including the harmonics (which are integer multiples of the defective frequency) and the amplitudes of the defective frequency and its harmonics, are subsequently employed in generating a degradation signal (Gebraeel N. , 2006).

(Zheng Y. , 2019). In this study, a predictive model for estimating the remaining useful life (RUL) of a bearing is developed. The proposed method incorporates a unique health indicator and a linear degradation model to accurately forecast the RUL. The utilization of the Hilbert-Huang entropy is employed in order to extract health indications and subsequently analyze the horizontal vibration signals acquired from the bearing. In the study, the author effectively demonstrated the utilization of the health indicator and degradation model for assessing the present health condition of bearings and making predictions regarding their Remaining Useful Life (RUL).

(Bejaoui, Bruneo, & Xibilia, 2021) This paper introduces a prognostic methodology for diagnosing broken rotor bar failures in rotating machines. The methodology encompasses the modeling of the failure mechanism, development of a health indicator, and the subsequent prediction of the Remaining Useful Life (RUL).The researchers employed a blend of signal processing methodologies, intrinsic metrics, and component analysis to effectively supervise the performance of the induction motor.

The deterioration patterns of crucial motor elements, such as stator current, torque, and speed indicators, were monitored and extracted utilizing time-frequency sensors. From this, the RUL for the motor can be accurately predicted. Experimental results corroborated the developed methodology, and they concluded that the prognostic approach is a useful tool to predict induction motor degradation.

To ensure the optimal and effective operation of machinery, equipment, infrastructure, buildings, or systems, various routine and necessary maintenance tasks must be performed. These tasks include inspections, cleaning, repairs, replacements, upgrades, lubrication, and adjustments. The cost of maintenance is typically a significant factor and is estimated to be about 4% to 15% of the overall running cost, depending on the specific industry (Mikler, 2011). According to (Mostafa, Lee, Dumrak, Chileshe, & Soltan, 2015), the maintenance cost can increase by 15% to 70% of the operational cost, depending on which production is carried out. For instance, in the States, approximately $200 billion is spent annually on the maintenance of production and facility machinery (Bevilacqua & Braglia, 2000).

These statistics highlight the substantial financial impact of maintenance activities on businesses and industries. They underscore the importance of implementing effective maintenance strategies to minimize costs, maximize operational efficiency, and ensure the longevity of assets and equipment. The main goal of most maintenance strategies is to prolong operational life of systems or equipment, minimize instances of downtime, and ensure their safe and reliable functioning. Another objective is to avoid or diminish the possibility of mechanical failures, malfunctions, or breakdowns. Thus, maintenance becomes a cost-saving strategy. By implementing effective maintenance practices, organizations can prevent costly disruptions, reduce the need for major repairs or replacements, and optimize the performance of their assets. This proactive approach helps minimize downtime, increase productivity, and avoid potential safety risks. Ultimately, Maintenance plays a pivotal role in guaranteeing the seamless functioning of systems and equipment, augmenting operational efficacy, and optimizing long-term cost savings.

2.4.2 Neural Networks

Neural Networks are an artificial intelligence technique that utilizes data from sensors to identify defects in system machines and characterize their functional conditions (Kaiser K. , 2007). Neural networks can be characterized as information processing systems comprising numerous interconnected processing elements that closely resemble the architectural organization of the cerebral cortex region of the brain. One of the essential functionalities exhibited by neural networks is their capacity to represent and simulate a given process utilizing real-time data. Additionally, they possess the ability to identify and extract patterns, irrespective of the presence of noise or gaps in the information received from the process. Moreover, neural networks also demonstrate the capability to interpolate and extrapolate beyond the training data that has been acquired. (Alguindigue, Loskiewicz-Buczak, & Uhrig, 1993).

They designed a vibration monitoring model that analyzes vibrations from operational machinery components. They demonstrated that it's possible to use neural networks to interpret data that are distorted and noisy from traditional vibration analysis. The researchers employed the recirculation algorithm for data compression and the backpropagation algorithm to execute the actual classification of the patterns.

(Sinha & Pandey, 2002) Developed a conceptual framework was constructed to anticipate the likelihood of malfunction for a subterranean pipeline infrastructure utilizing an artificial neural network. Artificial neural network is trained using data collected from the field in describing the conditions of deteriorated pipelines due to rusting in real time. A probabilistic simulation framework is developed, that aims to estimate the reliability of pipelines for various adaptable connection. Several tests were carried out, which gave very accurate results in predicting pipeline failure with respect to the depth and length of corrosion. Using the current motion signature (Bansal, Evan, & Jones, 2004) employed a neural network approach to predict machine (DC motor) system parameters. He used real-time experimental data to train a neural network, which could detect abnormalities.

2.4.3 Markov Processes

Markov process is a widely employed probabilistic models in predictive maintenance to anticipate the future condition of equipment based on its condition state. They offer valuable insight to operators for planning maintenance activities, minimizing downtime, and enhancing overall equipment efficiency. Studies have assessed the effectiveness of this approach. For example, (Gorjian Jolfaei, Rameezdeen, Gorjian, Jin, & Chow, 2022). A Markovian methodology was suggested to forecast the remaining useful life (RUL) of industrial pumps. His study utilizes series of observed data on pump failures to construct a Markov transition matrix to estimate the RUL.

Another study by (Aizpurua, et al., 2022) A multi-state Markov model was employed to make prognostications regarding the Remaining Useful Life (RUL) of aircraft engines. He estimated a transition probabilities between different health states of the engine to forecast its RUL. Furthermore, (Chan & Asgarpoor, 2006) conducted a case study on utilizing Markov processes in predicting the maintenance requirements of a fleet of trucks. The study employed Markov chains to establish the probability of truck failure and estimate the downtime required to carry out each maintenance activity.

CHAPTER 3

3. PROBLEM DESCRIPTION

Maintenance issues in industrial sectors can lead to various unfavorable outcomes, including decreased productivity, increased operational expenses, and compromised well-being and safety of workers. Neglecting or inadequately addressing maintenance concerns can result in equipment malfunctions, operational breakdowns, and potentially life-threatening incidents. A prevalent issue within the field of maintenance pertains to the absence of proactive measures aimed at preemptively addressing potential problems. Many industries adopt a reactive maintenance strategy, where equipment is repaired and restored only after it has mechanically failed. This reactive approach leads to higher repair costs, increased frequency of repairs, and extended periods of production downtime. Industries become susceptible to sudden failures and disruptions in their operations when routine maintenance protocols are overlooked.

Another significant issue revolves around the inadequacy of training and expertise among maintenance personnel. Maintenance staff may encounter difficulties in identifying equipment problems or performing effective repairs if they do not have a comprehensive understanding of the equipment they are responsible for. Insufficient training can result in the incorrect use of tools and equipment, exacerbating maintenance problems.

Furthermore, many industries often struggle to effectively manage their maintenance schedules. Inadequate planning and coordination can lead to the postponement or neglect of maintenance activities. This can result in a backlog of pending tasks, increasing the risk of equipment malfunctions and causing operational disruptions. In sectors where uninterrupted operations are essential, such as manufacturing facilities, delaying or ignoring maintenance activities can have severe consequences for production efficiency.

In addition, some industries face challenges related to the accessibility and procurement of maintenance spare parts. Maintaining an inventory of spare parts can be financially burdensome, especially for complex and specialized equipment. Insufficiently stocking an adequate supply of spare parts often leads to extend periods of machinery downtime, as the necessary replacement components must be sourced externally or manufactured.

Moreover, the proliferation of advanced technologies and complex machinery has introduced new challenges for maintenance personnel. Successfully implementing technological advancements like, the Internet of Things, automation and predictive maintenance systems requires specialized knowledge and skills in troubleshooting and maintaining these intricate systems. Failing to comprehend and adapt to these technological advancements may result in a lack of proficiency in identifying equipment malfunctions or leveraging the benefits of predictive maintenance strategies.

Lastly, industries are increasingly grappling with sustainability and environmental issues related to maintenance practices. Properly disposing of and recycling maintenance waste, including lubricants, chemicals, and old equipment, is of critical importance due to the need to comply with environmental regulations. Neglecting to address these concerns appropriately can lead to legal liabilities, damage to reputation, or adverse environmental impacts. To address these challenges, it is imperative to implement a predictive maintenance policy capable of anticipating impending failures and conducting maintenance operations prior to any system breakdown.

For example, (Kaiser & Gebraeel, 2009) a simulation study was conducted in order to investigate the effects of different maintenance policies on the reliability and performance of a manufacturing system comprising multiple parallel workstations. Specifically, the present study was concentrated on investigating the efficacy of degradation model-based approaches in formulating predictive and preventive maintenance policies.

In the course of simulating multiple maintenance policies, a comparative analysis was carried out to assess the influence of various policies on system performance. This assessment took into consideration factors such as the frequency of equipment failure replacement, scheduled equipment replacement, routine maintenance frequency, and the associated cost for each maintenance policy. The analysis was conducted at system reliabilities of 70 and 90 percent. However, Additional research is necessitated in order to assess the impacts of different maintenance strategies on the dependability of manufacturing systems functioning in both series and series-parallel arrangements. This study is designed to assess the importance of various maintenance strategies about the performance of chemical production line, with a specific focus on a case study involving a series-parallel arrangement of workstations.

The research focuses on investigating the application of predictive maintenance, the implementation of predictive maintenance strategies in Cameroon, Africa is observable to be in its nascent phases and represents an emerging field of study.This observation is based on an examination of scientific research conducted in this field. The fundamental aim of this research endeavor is to assess the Remaining Useful Life (RUL) of bearings within pivotal machinery employed in industrial installations. We will utilize the bearing degradation signal to simulate a predictive maintenance policy for the system and conduct an extensive comparison with the existing maintenance policy currently implemented as the prevailing strategy for plant maintenance.

CHAPTER 4

4. METHODOLOGY

4.4 Determination of the RUL of the Rotating Element Bearing

A rotating element bearing is a mechanical device commonly used to provide support for the rotational motion of an element, such as a shaft. Its primary purpose is to minimize friction and facilitate smooth movement. This bearing has the capacity to withstand a load of 10 kilonewtons (KN), which is approximately equivalent to 2248.8 pounds of force. The bearing assembly consists of several essential components, including a typical rolling element bearing consist of an outer race, an inner race, rolling elements (balls or rollers), a cage for the purpose of segregating the rolling elements, and a lubricant aimed at diminishing friction and dispersing heat.

Typically, in its structural configuration, the outer race remains stationary, while the inner race facilitates the rotation, enabling the movement of the element it supports, such as a shaft or axle. When a load of 10kN is applied to the rotating element bearing, the rolling elements effectively distribute the load uniformly, thus reducing pressure and preventing undue wear or damage to the bearing surfaces.

The robust construction and high-quality materials of the bearing ensure its ability to withstand the specified load without compromising its performance or durability. To optimize performance and minimize potential degradation, it may be necessary to periodically apply lubrication to the bearing of the rotating element to maintain a low-friction environment. This practice contributes to the reduction of heat generation and prevents premature failure resulting from excessive wear between the various components of the bearing **Figure 4.1** explains the Rotating Element Bearing.

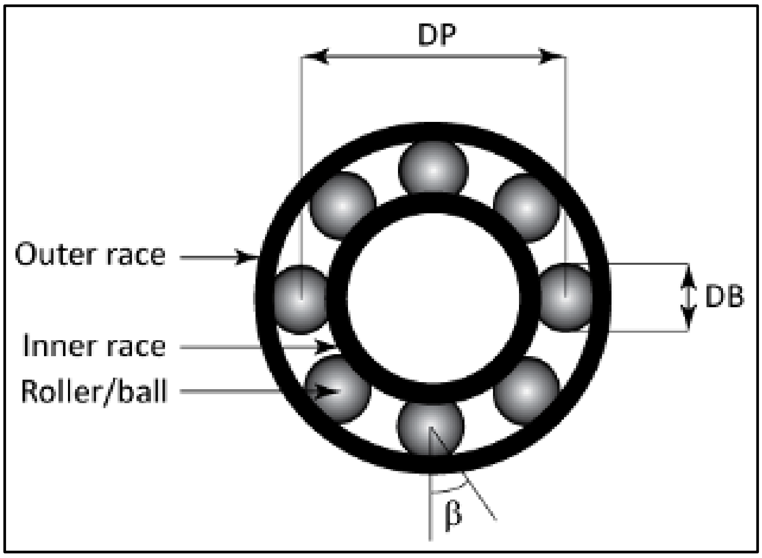

Figure 4. 1 Rotating Element Bearing

Source: Moler, C. (1970). *MathWorks, Inc.,*. Retrieved from MATrix LABoratory.

4.4.1 Experimental Procedure

1. The rotating element bearing was installed on a test dynamometer, ensuring it is properly aligned and mounted.

2. The accelerometers were affixed to the bearing housing in order to acquire vibration data corresponding to the bearing's performance during operation.

3. This bearing was run at a specified standard operating condition, known as the baseline condition, without any degradation.

4. The vibration signals from the sensors were collected and recorded during this uninterrupted operation for 5 minutes. This baseline measurement will serve as a reference for future comparisons.

5. Degradation was gradually introduce to the bearing by inducing faults. This was achieved by applying controlled forces or introducing artificial faults such as bearing defects or contaminants.

6. Once the desired degradation level is achieved, the bearing was run and vibration signals were collected using the sensors. This was done for 5 minutes daily for a duration of 30 days.

7. The collected data was in the form of an excel file which was then plugged into Matlab for processing and visualizing the degradation profile of the rotating element bearing.

4.4.2 Expression of Results

(Gebraeel N. , 2006) This study expatiates on an exponential degradation model which was developed to elucidate the progression of degradation in a rotational element bearing over the course of its operational duration.

The author defined degradation as a stochastic process, denoted as $A = \{A(t), t > 0\}$ where $A(t)$ represent the signal from degradation, one must consider the amplitude of the signal at a particular point in time t.

This deterioration signal is modelled as

$$\boldsymbol{A(t) = h(\emptyset, \theta, t) + \varepsilon(t)} \tag{4.1}$$

Here h (.) characterizes the component's characteristics in relation to time and the vibration amplitude of the component.

The exponential degradation model posits that the vibrational amplitude of the bearing was measured at distinct time interval $t1, t2 \ldots \ldots tn$ consider$t \geq 0$,

The models have an amplitude which follows:

$$\boldsymbol{A\ (t_n) = \emptyset + \theta e^{\beta t_n + \varepsilon(t_n) - \frac{\sigma^2}{2}} = \emptyset + (\theta e^{\beta t_n})(e^{\varepsilon(t_n) - \frac{\sigma^2}{2}})} \tag{4.2}$$

In the aforementioned equation, the parameter, $\emptyset$ retains a constant deterministic quality, while θ, β assumes the nature random variables. Furthermore, the error term $\varepsilon(t_n)$ is characterized by a mean of 0.

From this equation, the author was able to describe the degradation path of the rotating bearing which predicts when this component would fail to obtain a more realistic Remaining Useful Life (RUL) for the bearing, the author incorporated sensory data collected from the bearing's operational environment. This facilitated the ability to modify and refine the degradation pattern, leading to a more precise determination of the remaining useful life through the utilization of the latest degradation characteristics.

The researchers took into account various sensory measurements including temperature, humidity, vibration, and other pertinent parameters to consider external factors that influence the rate of degradation. They integrated this sensory data into a residual life distribution model, representing the cumulative probability distribution of residual life. This residual life distribution is characterized by exponential degradation patterns can be updated by incorporating sensory data, which can be expressed by the subsequent mathematical;

$$R(\left(\frac{t}{S(t)}\right) = S(t) * e(-\lambda t) \quad \textbf{(4.3)}$$

Where:
R (t|S (t)) represents the useful life function time t, written S(t).

S(t) characterizes the state of bearing or gear with time, t

λ is degradation rate parameter determining the rate of component deterioration.

t0 represents the initial time when the sensory data is collected.

The equation presented herein integrates sensory information denoted as $S(t)$ with an exponential degradation pattern, facilitating the computation of useful life distribution pertaining to a machine component.

The exponential degradation model equation for a rotating element bearing is given as: $\boldsymbol{D(t) = D_0 * e^{-\lambda t}}$ **(4.4)**

$D(t)$ is desired level of deterioration at time t, Do is the start of deterioration at time t=0, λ is the degradation rate constant and e is the error term (approximately 2.71828) to experimentally determine the degradation profile, the degradation level can be measured at specific time intervals. Mathematically:

$$\boldsymbol{Degradation\ level\ at\ time\ tl : D(t1) = D0 * e\text{^}(-\lambda t1)} \quad \textbf{(4.5)}$$

$$\boldsymbol{Degradation\ level\ at\ time\ t2 : D(t2) = D0 * e\text{^}(-\lambda t2)} \quad \textbf{(4.6)}$$

$$\boldsymbol{Degradation\ \ level\ at\ time\ tn: D0 * e\text{^}(-\lambda tn)} \quad \textbf{(4.7)}$$

These degradation levels can be plotted against time to visualize the degradation profile. The slope of the line in an ln (D) vs ln (t) plot represents the degradation rate constant, λ.

4.4.3 Estimation of the RUL

The RUL of the bearing was determined using the formula

$$\boldsymbol{RUL = \frac{estimated\ degradation\ level}{initial\ degradation\ level} * 100} \quad \textbf{(4.8)}$$

4.5 Vibrational Profile of a Rotating Element Bearing

The vibrational profile of the bearing was simulated over a 30 days duration, during which 10,000 measurements were recorded to capture the amplitude. This extensive dataset provided a comprehensive representation of the bearing life cycle. The MATLAB codes will be utilized to educate the entire process**. Figure 4.2** is depicting generating vibrational profile of this rotating element bearing, starting from a healthy state, and progressing towards a faulty state. This profile was obtained using our synthetic degradation mat file.

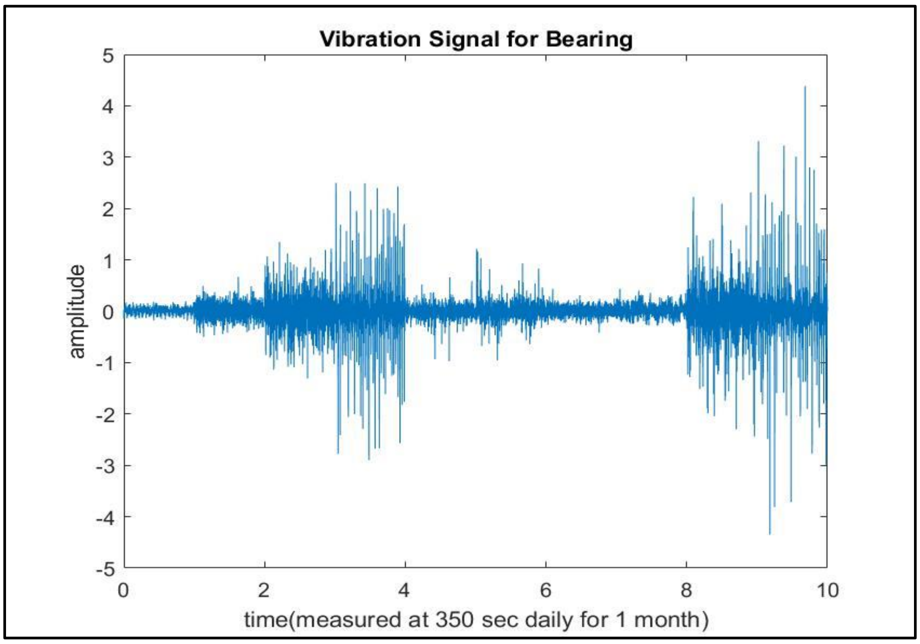

Figure 4. 2 Rotating Element Bearing Vibrational Signal

Apparently, the vibration amplitude increases with time, hence progressive degradation of the bearing. The higher peaks in amplitude correspond to an intensified vibration in the rotating element bearing. As previously highlighted, vibration is a critical factor contributing to the faulting of the bearing and the gear reducer. This observation emphasizes the significance of time, vibration frequency, standard current, and torque as the most influential factors in the degradation model.

We used sensors to record the bearing's amplitude for 350 seconds daily over the course of 30 working days. These parameters were considered comprehensively, recognizing that conditions may not remain constant every day. Variables such as intermittent generator connections, which lead to split-second exchanges, were also factored into our calculations. The compensation factor takes into consideration the discrepancies in duration when evaluating the Remaining Useful Life (RUL), it is intrinsically contingent upon the machine's operating time.

4.6 Estimating Remaining Useful Life

To estimate the Useful Life of the bearing and determine the machine run time, scheduling maintenance, will be the first step when computing the complete deterioration life span of the bearing. Utilizing MATLAB, we computed the degradation life cycle of the bearing to be 73,320 minutes $maximum\ life\ span\ 1222 hours * 60$. This duration represents the point at which the bearing is expected to fail, which can be attributed to wear and tear or loss of lubrication. To fine-tune our model, the degradation constants were $\lambda = 0.1$ and the noise factor$\beta = 0.01$. Subsequently, after determining the degradation life cycle of the bearing, we generated an RUL graph to visually represent the overall progression of the bearing's lifespan leading up to the anticipated failure point. This graphical representation allowed us to precisely identify the moment when the bearing is likely to experience a breakdown, facilitating proactive maintenance scheduling. **Figure 4.3** illustrates the RUL of the rotating element bearing.

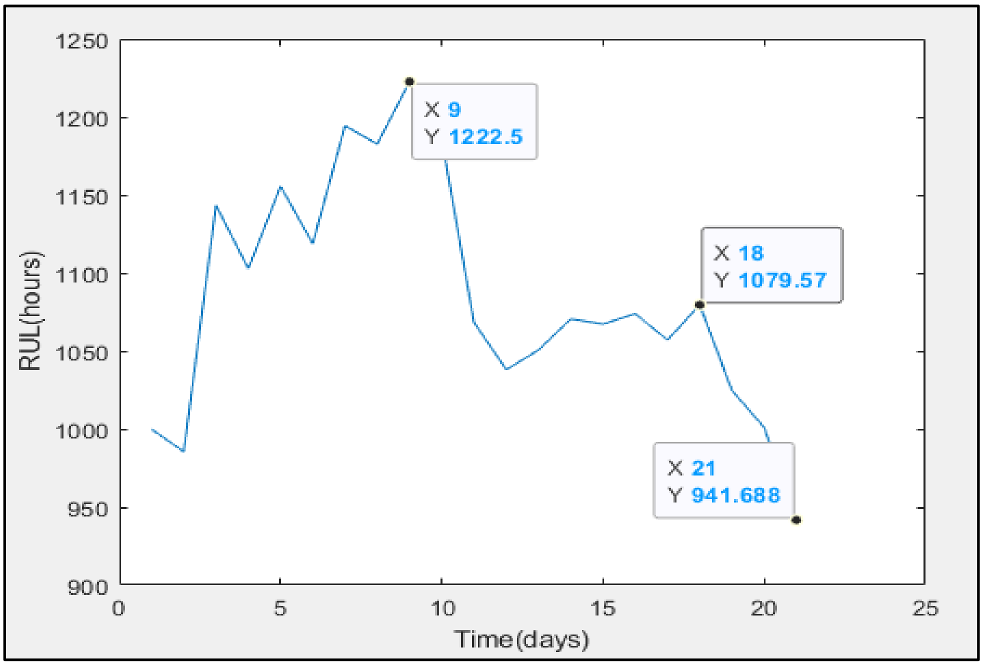

Figure 4. 3 Remaining Useful Life for Rotating Element Bearing

From the graph, the bearing has a total lifespan of 1,222 hours. Throughout our experimentation, the bearing exhibited a remaining useful life (RUL) of 942 hours, signifying a degradation of approximately 23%. From this data, the bearing is likely to fail around the 91st day. Consequently, it is advisable to schedule maintenance for the 90th day, which correspond to 3 months. This is an approach to ensuring the reliability of the manufacturing system.

CHAPTER 5

5. SIMULATION STUDIES

5.1 Description of the Production Process

The solution concentrate line produces solution concentrates, often labeled as SL, which are homogeneous liquid preparations intended to be use as a true solution of the active ingredient after dilution with water. Most SL products are formulated with built-in biological enhancers that enhance the biological efficacy of the active ingredients. An example of a biological enhancer used in the formulation of SL is alkyl phenol and silicone spreader, which acts as a spreader and sticker, aiding in the quick absorption of the active ingredient into the leaves while providing rain fastness. One such Holfarcam product formulated as an SL is Glyphosate 360 SL, a nonselective and systemic herbicide used for controlling perennial weeds in agriculture and lawns.

The production process for a 1000-liter batch is as follows: The reactor is initially filled with 50% softened water, achieved through water hardness reduction via ion exchange. The reactor motor is started at low speed. The active ingredient, in powder form, is added to the reactor while stirring continues. The reactor is sealed, and the base is introduced into the reactor through pipes connecting the base tank and the reactor. To manage the heat generated during the reaction, chilled water circulates through the reactor until the temperature drops to room temperature. Other additives, such as surfactants and colorants, are incorporated and stirred to achieve a homogeneous solution. At the end of the reaction, the solution is pumped through a filter, aided by a diaphragm pump, to remove any undissolved additives. The final product is stored in a storage tank, allowing any remaining moisture to evaporate and the raw acid to complete its reaction with the base before being filled into packaging containers. This is done after a sample has passed through the laboratory for various tests, including pH, persistent foam tests, and suspensibility.

Once all these quality standards are met, the product is ready for the market. It's crucial to emphasize the significance of the chemical reactor compartment as it plays a vital role in determining the production of SL. This is where the chemical reaction (neutralization) takes place. Without the proper functioning of the chemical reactor, the production process for SL could be significantly disrupted or even halted. Therefore, it is essential to prioritize the maintenance and predictive maintenance of the chemical reactor when producing SL.

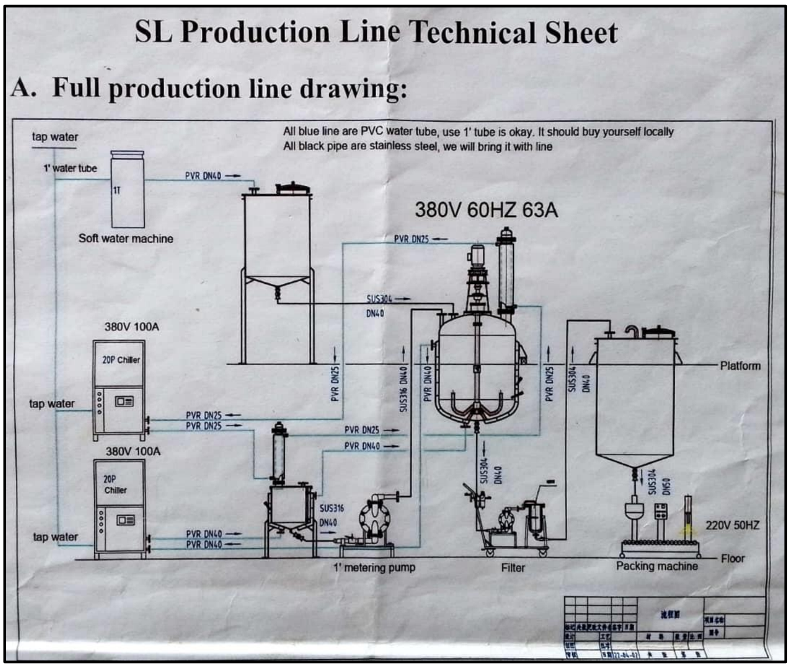

Figure 5. 1 Production Process for Solution Concentrate

5.2 Simulation And Analysis Of Maintenance Policies Series-Parallel Workstation

This section, a comprehensive assessment of the performance in the solution liquid production system was carried out. This product line has three work cell, each of which contains duplicated workstation. To facilitate this analysis, we utilized the ARENA simulation software as our simulation tool. When assessing the reliability of the production system, we examined a network configuration that combines both series and parallel workstations as that of the practical Holfarcam Sarl production line setting.

5.3 Manufacturing System

The solution liquid concentrate production line is the manufacturing system under analysis, having three operational work cells. It started by work cell 1 having a single work station, similar scenario applies for work cell 2 but for work cell 3 there are two work stations. When the pre-processed component is delivered at the initial work cell, it undergoes processing at workstation 1. The subsequent step involves the processing of the component at workstation 2 and subsequently at workstation 3. The decision as to whether it will be processed at workstation 3 or 4 depends on the availability of either workstation. Ultimately, the component is transferred to the warehouse for further distribution. **Figure 5.2** is a representation of Holfarcam Sarl manufacturing system.

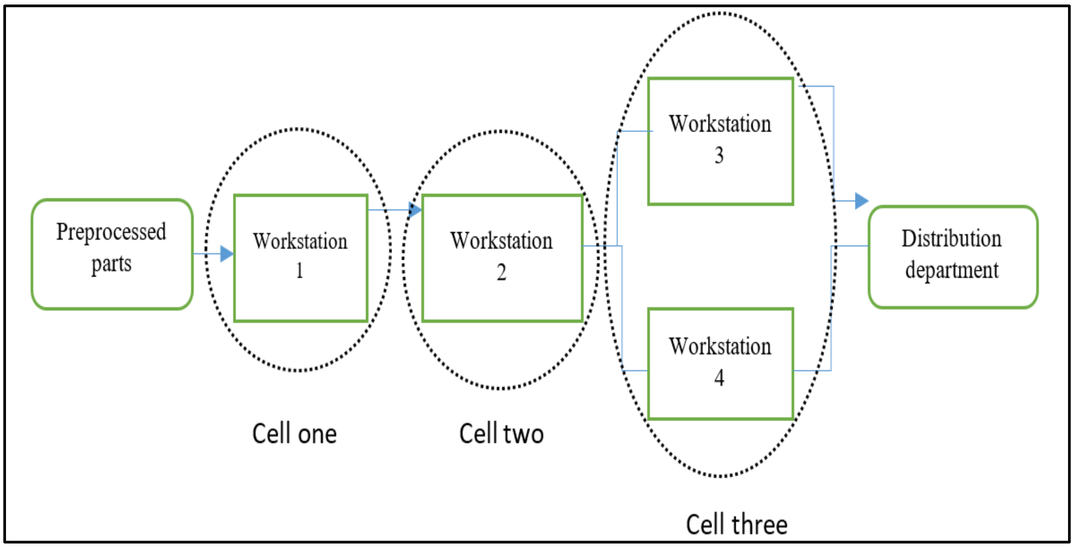

Figure 5. 2 HOLFARCAM Sarl Manufacturing System

5.4 System Reliability

In a series- parallel system, the system's components are arranged in both series and parallel relationships. Considering **Figure 5.3** below, the reliability of the *ith* component is denoted as;

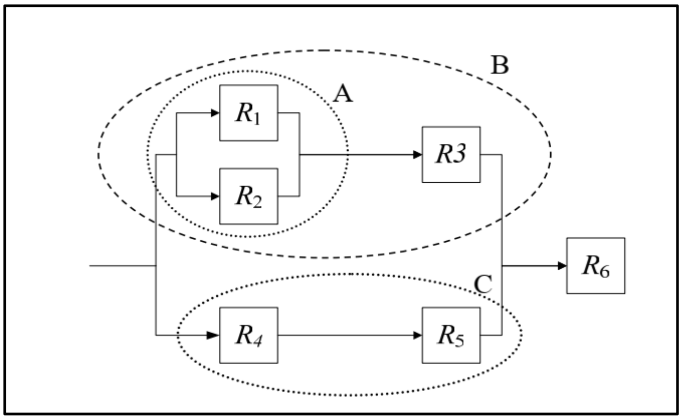

Figure 5. 3 Illustration of Series-Parallel Configuration

To assessing reliability, one approach is to break down the network into parallel and series subsystems. Evaluating this reliability involves examining their separate reliabilities of various subsystems and then taking into account their interdependencies to calculate the overall system reliability. For the network depicted above, the reliability subsystem is as follows:

$$\boldsymbol{R_A = [1 - (1 - R_1)(1 - R_2)]} \quad \textbf{(5.1)}$$

$$\boldsymbol{R_B = R_A\,(R_3)\ ,\ R_C = R_4\,(R_5)} \quad \textbf{(5.2)}$$

$\boldsymbol{Since\ R_B\ and\ R_C\ are\ in\ paralle\ with\ one\ another\ and\ in\ series\ with\ \ R_6,}$

$$\boldsymbol{R_S = [1 - (1 - R_B)(1 - R_C)](R_6)} \quad \textbf{(5.3)}$$

The manufacturing system been analyzed is illustrated in **Figure 5.2.** This configuration comprises a sequential arrangement of two workstations, succeeded by a parallel configuration of two additional workstations. Based on the present configuration, in order for system failure to transpire, it is imperative that one of the ensuing conditions be satisfied:

1. **Workstation 1 fails**
2. **Workstation 2 fails**
3. **Workstation 3 fails**

To determine the system's reliability, we evaluate the reliability of individual workstations at a given time "t" using probability calculations that consider the specific configuration of each system component. The resulting overall system reliability, denoted as$R(t)$, is calculated as follows:

$$\boldsymbol{Rs(t) = (R1(t).R2(t).[1 - (1 - R3(t)\big(1 - R4(t)\big)]} \quad \textbf{(5.4)}$$

$\boldsymbol{where, Ri(t)\ is\ the\ reliability\ of\ the\ ith\ workstation}$

5.5 The Simulation Model

The simulation was carried out using the ARENA simulation software. The production system being investigated can be described as a simulated configuration with a series-parallel structure, consisting of four discrete workstations. Pre-processed items are transported to a staging facility, the time intervals between the arrivals of the entities are characterized by an exponential distribution, with an average value of 0.25mins. Upon the onset of the process, every individual component is allocated to its corresponding initial workstation.

Afterward, the component proceeds which undergoes processing at the second workstation, and subsequently, it undergoes processing at one of the final two workstations depending on their availability (not processing any pre-processed parts).Certain assumptions were considered about the processing times at each workstation. Workstation 1, which is the chemical reactor, was assumed to have processing times following a triangular distribution (it assumes three parameters, the minimum value, maximum value and the peak or the mode) with parameters of 3.25mins, 3.50 mins and 4.20 mins. Similarly, the processing time at workstation 2 follows a triangular distribution of values of 2.5, 2.75, and 3.0 minutes. Additionally, workstations 3 and 4 were assumed to have processing times following a triangular distribution (distribution percentages: as 75% and 25%, respectively for one liters and five liters of the final product) with parameters of 4.75, 5.25, and 5.75 minutes. Upon completion of the production process, the final product are transferred to their designated shipping blocks.

In manufacturing industries, the production line can experience periods of unavailability as result of unplanned or planned maintenance routines. The duration of downtime resulting from a system failure is regarded as stochastic, adhering to a Normal distribution characterized by a mean of 300 minutes and a variance of 30 minutes. The downtime resulting from scheduled maintenance routines is also stochastic, having mean 30 minutes and variance of 5 minutes. Conversely, the occurrence of unforeseen system failure is expected to lead to increased downtime, as a result of the unforeseen need for replacement components and maintenance assistant.

Next, it was assumed that every work station undergoes gradual degradation until it eventually ceases to function. The degradation of workstations is presumed to be represented by the exponential degradation model, which uses real vibration-based data. Specifically, Degradation signals extracted from vibration-based data, alongside their respective failure times, are utilized to illustrate the progression of deterioration. This simulation model consists of three distinct sub-models, each serving a specific purpose. The initial sub-model replicates the manufacturing system under simulation, the second sub-model delineates the control logic inherent in the maintenance policy. Finally, the last sub-model governs the repairs activities in the production line.

5.5.1 Manufacturing System Sub model

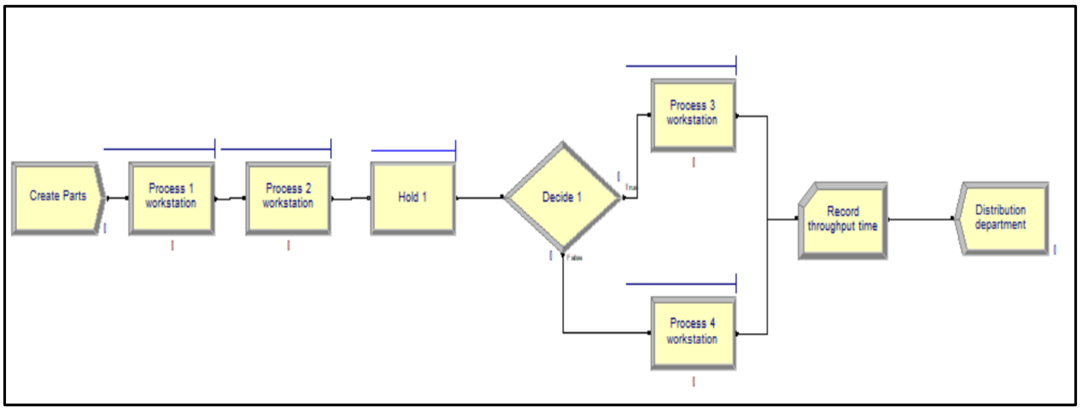

Figure 5. 4 Manufacturing System Sub model

Every initial entity is been generated by the CREATE block and prepared for processing. Once the entities are generated, they are sent to the first processing workstation (process 1). Following processing at process 1, they proceed to the second processing workstation (process 2), where they enter a hold or waiting state. The HOLD is been used to monitor their usage levels at various workstations using ARENA expressions.

$$\boldsymbol{NQ(Process\ 2\ workstation.Queue) <= 10\ \&\&\ NR(Resource\ 1) <= MR(Resource\ 1)} \quad \textbf{(5.5)}$$

$\boldsymbol{NQ(Process\ 2\ workstation.Queue)}$ **:**

This module provides the current count of entities that are currently in the queue associated with the Process 2 workstation. The queue serves as a designated buffer for holding entities that are awaiting processing by the workstation.

$\boldsymbol{NR(Resource\ 1) <= MR(Resource\ 1)}$ **:**

Evaluates to TRUE if the number of busy resource units (NR) of Resource 1 is less than or equal to the capacity of Resource 1 (MR) in process one workstation.

After entities have been processed at workstations 1 and 2, regulated by the HOLD module, the process enters a DECISION module that determines the processing at workstation 3 or 4 based on a predefined quantity processed by each workstation. Workstation 1 follows a triangular distribution with parameters of 3.25, 3.50, and 4.20 minutes. Similarly, at workstation 2, it is assumed that the processing time is subject to a Triangular distribution with parameters of 2.5, 2.75, and 3.0. Additionally, workstations 3 and 4 have processing times of 4.75, 5.25, and 5.75 minutes while assuming triangular distribution.

Upon completion in processing these parts, these finalized entities proceed to a RECORD module responsible for monitoring and recording the overall throughput of the system. Throughput is calculated as throughput = throughput + 1. Subsequently, the entities are removed from the production process line via the DISPOSE block.

5.5.2 Manufacturing System Sub model

These sub-models simulate the failures of various workstations within the system and simultaneously determine maintenance activities, two subroutines assist in this process: the first subroutine generates workstations failures, and the second one shuts down the workstation. Below are the sub models for the degradation model.

a. Simulation of the manufacturing system using the exponential degradation model.

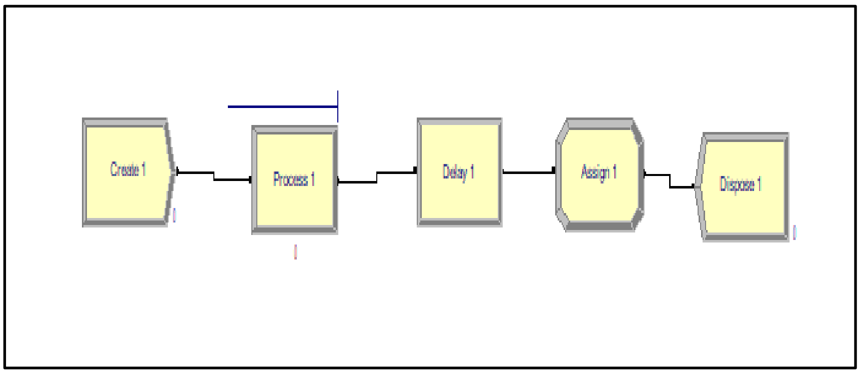

Figure 5. 5 Exponential Degradation Model.

The provided simulation code in **Figure 5.5** represents a system in which progressive degradation follows an exponential pattern throughout its operation. The initial value of the system state variable is set to 100.0 (when the component is in a good state), and the exponential degradation rate is configured as 0.05. The simulation generates an entity at regular intervals of 1 time unit, after which each entity is subjected to a delay of 1 time unit. During this delay period, the system state variable experiences degradation that follows an exponential decay pattern. Following the delay period, the entity is effectively disposed.

To collect simulation results, an iterative process is employed over the entities within the simulation. This process involves accessing the state attribute of each individual entity. Analyzing the simulation results provides a comprehensive understanding of the system's state, which results from exponential degradation.

b. Failure Routine Sub model

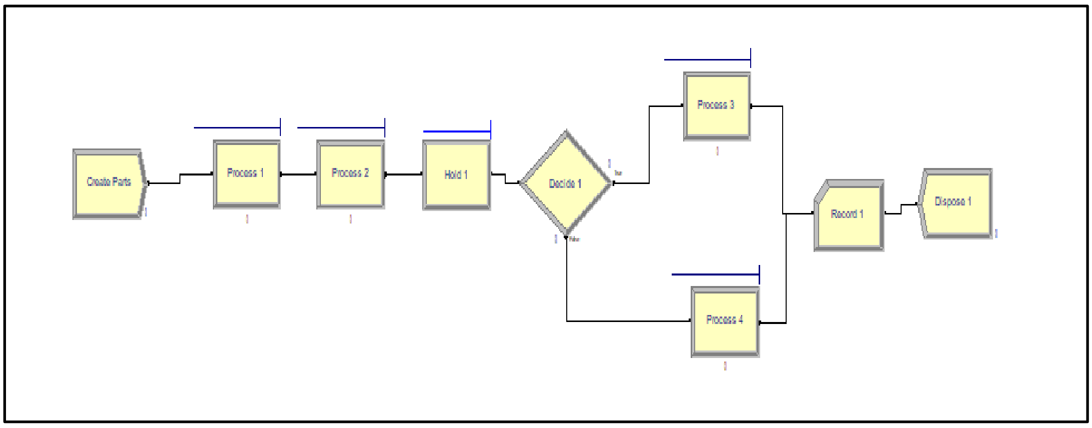

Figure 5. 6 Failure Routine Submodel

The failure routine sub-model in **Figure 5.6** the condition of the manufacturing system upon the occurrence of a prospective malfunction in the course of the production process. The subroutine starts at the CREATE block which generates its entity with a value 5 at the beginning of a simulation run. A failure routine is implemented on Process 1 to address system failures effectively. This choice is made because Process 1 is a critical asset in the manufacturing line. The parameters for the failure subroutine include 8 hours of uptime and an exponential downtime with a mean of 25. The results of the simulation are displayed on a graph. When there is an accumulation at Process 1, the number in waiting increases, signifying a problem along the chain, and the system becomes idle.

The failure time subroutine, as shown, is accountable for simulating workstation failures and determining the system's preventive maintenance (PM) interval. The process starts by using the CREATE block which creates an entity. The management of the generation of failure occurrences in workstations and the scheduling of routine preventive maintenance (PM) within the system are undertaken by the entity.

ba. Preventive Maintenance Policy

Preventive Maintenance (PM) policy, the expedient incorporation of a phantom entity is expeditiously embedded within a Visual Basic Application code at the initial time (t = 0). The provided code excerpt of a Visual Basic Application effectively incorporates the generation and occurrence of unplanned downtime experienced by a workstation labeled as $failure\_time\_i$ and computationally determine the interval for preventive maintenance for the system, denoted as $pm\_interval$ workstations are susceptible to unforeseeable malfunctions, and it is postulated that the Weibull distribution serves as the fundamental model for the probability distribution of system failure durations. The shape parameter is denoted as β and the scale parameter goes as θ. The study estimated β = 1.0549, and the scale parameter is estimated to be θ = 90.784. The aforementioned parameters are derived through the utilization of a set of failure times from the rolling element bearing, thereby providing estimates for said parameters.

The system's preventive maintenance interval varies based on different levels of reliability. The system preventive maintenance (PM) interval is determined by solving for the time "t" with $Rs(t)$ representing the reliability of individual workstations (i = 1, 2... 4), in accordance with the specified system reliability level, $Rs(t)$ .The computation for determining the reliability of individual workstations is conducted by employing the expression of the DM policy. For unplanned downtime, the duration of $pm\_interval$ > failure time for every work station"i".

bb. Degradation Maintenance Policy

In this policy, the determination of the reliability of individual workstations is based on an examination of their respective degradation signals. Phase II data is utilized to calculate residual life, facilitating the determination of the reliability distribution for the workstation. Real-time observation of the degradation signal enables continuous updating of the reliability distribution for each workstation. This maintenance policy assumes the use of a condition monitoring system to capture data at one-minute intervals.

The generation of a phantom entity arises as a consequence of the failure time subroutine, wherein a two-minute delay is enforced before its integration into the Visual Basic Application block. The reliability of each workstation is calculated at regular intervals of two minutes using the Visual Basic Application algorithm, which is implemented through one of the prescribed methodologies;

1. The deterioration characterized with non-defective (phase 1) at the ith workstation, it is assumed the reliability of the workstation.

2. The deterioration characterized defective phase (phase 2) at the ith workstation assumes a reliability expressed in equation **(5.4).**

3. The deterioration pertaining to failure threshold (phase 3), at ith workstation, assumes reliability to be zero.

After conducting the assessment of reliability for individual workstations, it becomes possible to compute the overall system reliability. The computation of reliabilities, $Rs(t)$, is achieved by applying $Rs(t) = R1(t) * R2(t) * \ldots . * Rn(t)$ which is generally an n mutual independent component in series of system reliability at time t, which incorporates the reliability values of individual workstations,$Rs(t)$, where i represents the workstation number ranging from 1 to 4.

The estimated values of the aforementioned parameters were obtained through the utilization of a representative subset of degradation signals extracted from the dataset pertaining to degradation. The computed values of the parameters are $\theta = -5.024$ and σ^2 = 0.00461. In order to effectively devise a routine for system maintenance, it is essential to temporarily suspend the updating procedure and utilize the most current system reliability distribution in order to ascertain the remaining longevity of the system. The time allocation for a predetermined maintenance schedule is calculated using the following methods.

$$\boldsymbol{pm\_interval = tk + tmedian} \quad \textbf{(5.6)}$$

$\boldsymbol{where, tmedian\ is\ the\ median\ of\ the\ reliability\ distribution}$.

c. Resource Shutdown Subroutine

The assigned probability of resource failure per unit of time is 0.1, and the allocated duration for repairing the resource is 10.0 units of time. The simulation generates a resource failure entity at a frequency of one over the probability of failure time units. In the context of resource management, the occurrence of a resource failure entity is temporally postponed for a duration of "$REPAIR\_TIME$" time units, after which it is subsequently disposed.

The process that seizes the resource before processing a task. If the resource is unavailable, the process waits until the resource becomes available. After processing the task, the process releases the resource. Data obtained from the simulation can be collected by iteratively accessing the attributes of the simulation's entities. One relevant example involves acquiring resource failure data by tallying entities classified as "$RESOURCE\_TIME$" the mean duration for resource restoration can be determined by computing the average time between occurrences of resource failures.

The findings of the simulation can then be examined to gain insight into the impact of resource malfunctions on the system. For instance, the results of the simulation can be used to determine the duration during which the system is not operational or to identify strategies for improving the system's ability to withstand resource failures.

d. System Maintenance Submodel

The sub-model designated for system maintenance endeavors to replicate and analyze various actions associated with the upkeep of a system. This subroutine commences with a CREATE block that generates a solitary entity at the initiation of every simulation iteration. The entity subsequently proceeds to a HOLD block, wherein it remains inert until the production line shutdown is activated.

Below are factors explaining unexpected production line downtime:

- System failure.
- Deliberate implementation of a system replacement.

As previously mentioned, the manufacturing system under investigation is susceptible to failure if Workstation 1, Workstation 2, or Workstations 3 and 4 experience failures. In the event of a system failure, any workstations that have not failed will promptly initiate a shutdown process, leading to an unforeseen termination of operations. The DELAY module is used to simulate a temporary disruption in operations, specifically designed to replicate the duration required for remedial actions and replacement processes.

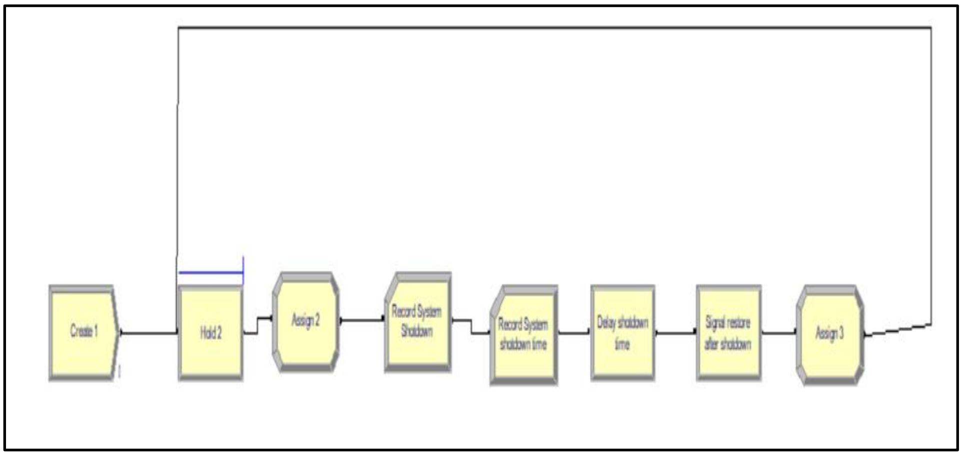

Figure 5. 7 System Maintenance Submodel

Following the occurrence of a delay, it is common to employ a SIGNAL block with the purpose of signaling the Resource Shutdown Subroutine to release its entities from the HOLD block it is currently occupying, thus allowing the workstations to become available once again, The occurrence of a system failure resulting in a period of operation disruption is deemed to be probabilistic in nature, adhering to a Normal distribution characterized by a mean duration of 150 minutes and a variance of 15 minutes. The Nf function evaluates cumulative count for unexpected downtime replacements and Nm function is for planned downtime.

CHAPTER 6

6. IMPLEMENTION AND RESULTS

Arena software was used in simulating the operations in the manufacturing system. For every simulation iteration it lasted for 30 consecutive days.

The frequency plot in **Figure 6.1** illustrates the failures associated with various maintenance policy, which were assessed to different reliability percentages, specifically at 55%, 65%, 75%, 85%, and 95%. The findings demonstrate that the adoption of a degradation-based predictive maintenance (DM) strategy leads to the least frequency of workstation failures across various system reliability levels. Additionally, the prevalence of malfunctions occurring at the 95% reliability threshold exceeds the frequencies observed at other reliability levels because of additional degradation indicators. The aforementioned instances of failures display a correlative decline in accordance with diminishing reliability standards.

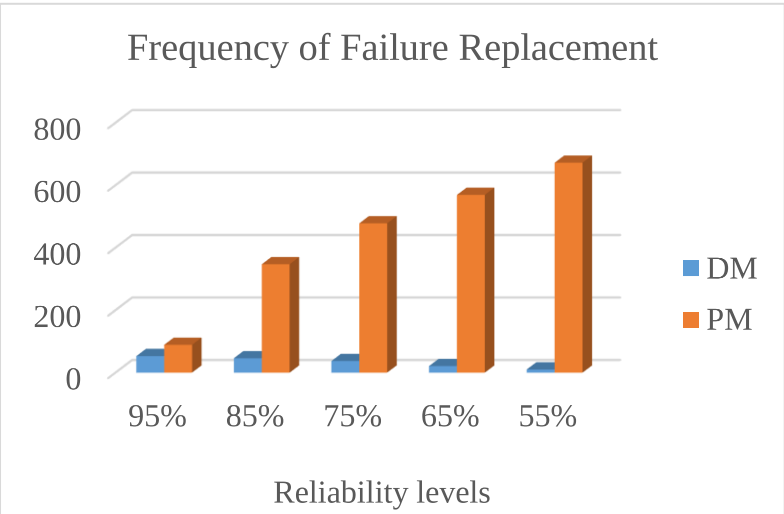

Figure 6. 1 Frequency Replacement for Failure

The data in **Figure 6.1** illustrate the count of scheduled maintenance procedures, Preventive replacements, specifically in the assessed manufacturing system pertaining to varying reliability levels, merit specific attention, the frequency for these replacements are related to the implementation of the Preventive Maintenance policy leads to a reduction in maintenance-related issues which decreases as the level of reliability diminishes. However, the maintenance policy pertaining to degradation showcases a distinctly contrasting pattern.

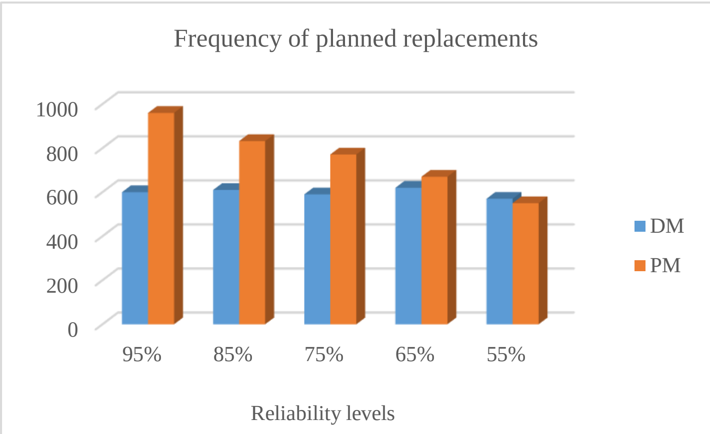

Figure 6. 2 Frequency Replacement for Planned Failures

Table 6.1 and Table 6.2 offers an empirical record of the means and standard deviations associated with the quantities of frequency replacements for failure and frequency replacements for planned are shown for each reliability level. The current study emphasizes that the DM Policy consistently results in lower standard deviations across most reliability levels. As a result, it indicates a reduced degree in the fluctuation of the number of maintenance procedures executed.

Table 6. 1 Means and Standard deviations,pertaining to the Frequency Replacements for Failure observed within different Levels of Reliability.

	Degradation.M.Policy (Nf)		**Preventive.M.POLICY (Nf)**	
Reliability %	**Mean**	**Standard.D**	**Mean**	**Standard.D**
95%	53	1.2	89	0.85
85%	46	0.67	347	1.23

Table 6. 2 Means and Standard deviations,pertaining to the Frequency Replacements for Failure observed within different Levels of Reliability (more).

75%	37	0.92	478	1.36
65%	21	0.88	569	0.87
55%	10	0.89	672	0.98

Table 6. 3 Means and Standard deviations,pertaining to the Frequency Replacements for Planned Failure observed within different Levels of Reliability.

	Degradation.M.Policy (Nm)		**Preventive.M. Policy (Nm)**	
Reliability (%)	**mean**	**standard.D**	**mean**	**standard.D**
95%	600	4.7	960	8.43
85%	610	3.4	832	6.71
75%	590	1.63	771	3.35
65%	620	2.32	670	4.54
55%	570	1.2	550	2.69

The assessment of the efficacy of maintenance policies was extended through the computation of the aggregate maintenance expenditures for each policy. The total maintenance costs, referred to as TC, are specified by the following definition:

$$\boldsymbol{TC = N_f C_f + N_m C_m} \qquad \textbf{(6.1)}$$

Where:

Nf Represents the quantity of system failures demanding replacement, in the provided context, Cf represents the cost associated with executing the procedure for addressing a system failure consisting of scheduled maintenance measures. ($600) was assumed, Nm signifies the amount of planned system schedule maintenance replacement,Cm and denotes actual amount attributed to the implementation of scheduled replacement ($50) was considered.

Overall amount associated with various maintenance strategies depends on it specified reliability percentage in the production line. The financial implications this maintenance strategy were assessed across 5 percentage levels their reliability percentages: 95%, 85%, 75%, 65%, and 55%. The results indicate that the DM policy results in significantly reduced overall costs at any given level of reliability compared to the PM policy. It's worth noting that the overall maintenance expenditure associated with the PM maintenance policy exhibits a decreasing trend as reliability improves. This is expected as higher reliability leads to a reduction in the occurrence of failures.

However, the scenario changes when considering Degradation maintenance (DM) Policy. In use of updating sensor-based procedure, one enhances the accuracy of the useful life distribution at the thresholds reliability. The incorporation of supplementary real-time degradation signals acquired from the monitored components (workstations) has facilitated the present study. The decrease in reliability levels corresponds with a reduction in maintenance costs associated with the DM policy. It is clear that the DM policy offers the most cost-effective approach to maintenance expenses.

Figure 6. 3 Total Maintenance Cost

Figure 6. 3 the statistical measures of the average and variability indicators for the aggregate maintenance expenses per policy, across different levels of reliability, are presented. An investigation of the collected data reveals the degree of variability observed in the overall maintenance cost is significantly reduced for most reliability levels when employing this repairs strategies which incorporates vibration sensors for updating useful life distribution.

Table 6. 4 Mean and Standard deviations explaining the Total Maintenance Cost at different Percentages of Reliabilities.

	Degradation.M. Policy TC		**Preventive.M. Policy TC**	
Reliability (%)	**Mean ($)**	**Standard.D($)**	**Mean($)**	**Standard.D($)**
95%	2540	233	4250	1254
85%	3620	327	4890	1210
75%	3870	457	5760	1455
65%	2100	124	9650	1327
55%	1540	93	10340	657

The utilization rate of a workstation refers to the percentage of time it is actively engaged in productive tasks, while throughput indicates the amount of work completed by a workstation within a specific time frame. These two metrics provide valuable information regarding the general productivity and efficiency of workstations within the system.

To assess the effectiveness of maintenance policies in practice, **Figure 6.4** displays the mean workstation utilization under various maintenance policies across different reliability thresholds, specifically 95%, 85%, 75%, 65%, and 55%. The analysis demonstrates that the implementation of the degradation model policy yields the utmost degree of workstation utilization.

Furthermore **Figure 6.5** is system throughput, the mean throughput associated with each maintenance policy is shown. The DM policy outperforms the PM maintenance policy in terms of improved performance. Additionally, the DM policy demonstrates lower maintenance costs and greater equipment availability, further contributing to its superiority over the PM policy. These findings suggest that implementing the DM maintenance policy is advantageous for optimizing performance and reducing equipment maintenance costs.

This finding suggests that applying this degradation policy will decrease cycle time compared to the conventional PM policy. **Table 6.4** presents the statistical summary of system throughput in terms of mean values and standard deviations.

Each policy is implemented at its corresponding reliability level within the framework. Based on our observations, it can be discerned that the implementation of a maintenance policy utilizing sensor-based updates of residual life distributions leads to reduced variability of throughput at majority of the reliability levels examined, specifically three out of five.

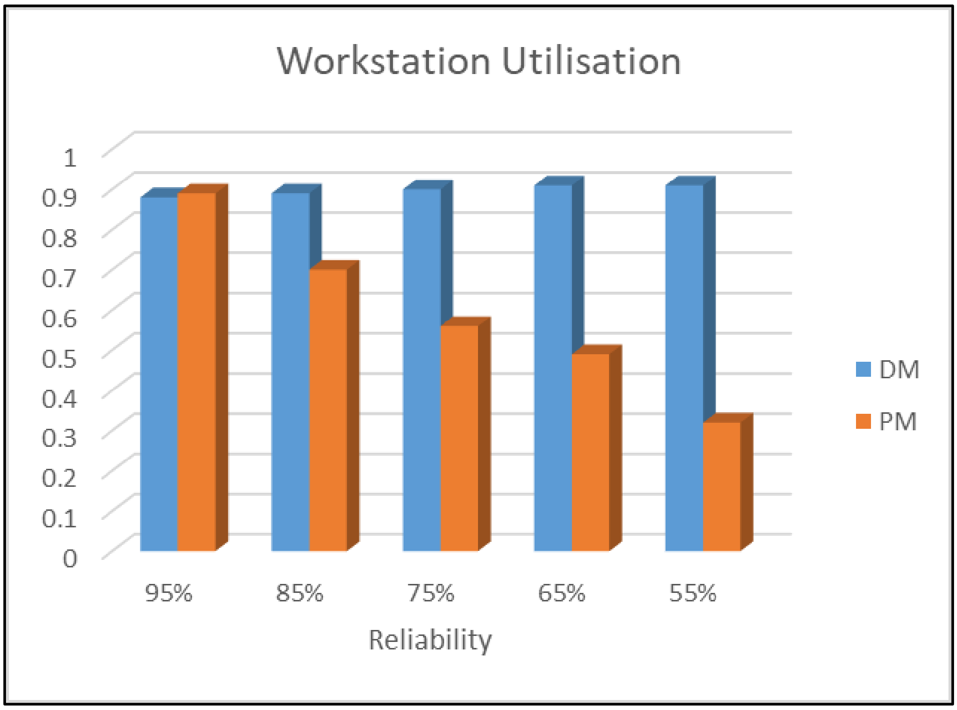

Figure 6. 4 Workstation Utilisation

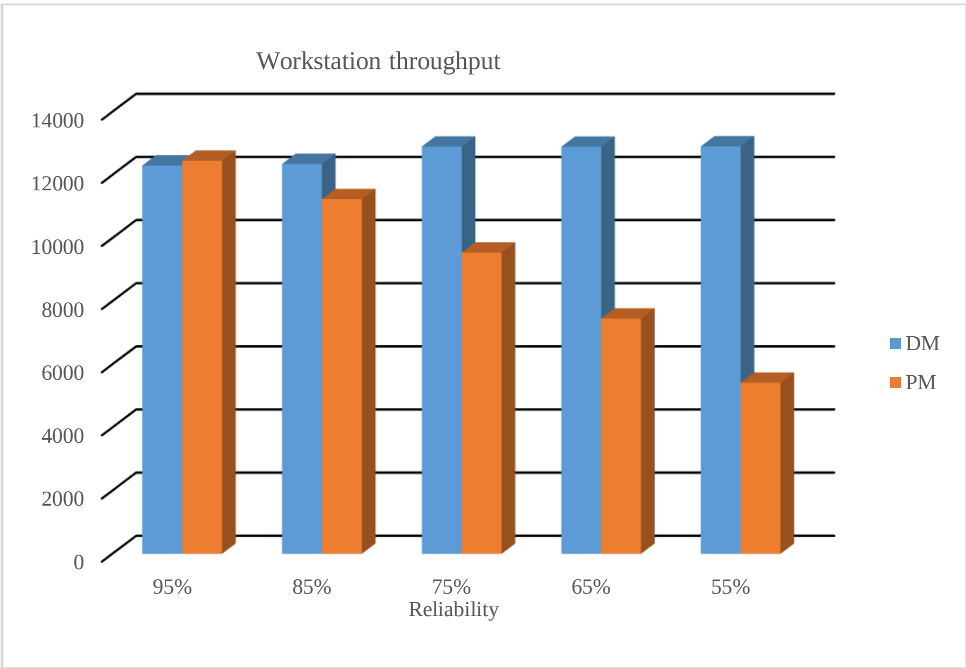

Figure 6.5 System Throughput

Table 6.4 provides a statistical summary of the system throughput, including mean values and standard deviations. Each policy is implemented at its corresponding reliability level within the framework. From observations, this type of maintenance policy which involves the updating of sensor of the remaining useful distribution reads low throughput variations in three reliability percentage points out of the total five used in the study.

Table 6. 5 Mean and Standard deviations the different policy production throughput and their reliability percentages.

	Degradation.M.Policy Throughput		**Preventive.M. Policy Throughput**	
Reliability (%)	**Mean**	**Standard.D**	**Mean**	**Standard. D**
95%	12300	672	12450	681
85%	12350	681	11235	579
75%	12900	783	9540	453
65%	12895	764	7450	342
55%	12905	691	5420	234

The primary objective of the simulation study using the degradation dataset is to assess the performance of degradation, with a focus on it importance of condition-based policy on the system reliability in the production system. This research made use of two maintenance strategy and evaluated their percentage reliabilities;

Firstly, maintenance routines are scheduled based on the reliability of the PM (Preventive Maintenance) policy. This policy considers Weibull failure times for workstation failures.

Secondly, Degradation Maintenance policy, it utilizes the dataset of real-time sensor to schedule maintenance routines. This policy, we update the residual life distribution using real-time sensory data because it enables more effective maintenance scheduling.

To assess the performance of the manufacturing system, several factors are analyzed, including failures workstation, planned workstation, maintenance policy cost, and utilization of workstation. This study offers a comprehensive insight into the system's performance and reliability. The overall analysis of this study reveals the sensory-updated degradation predictive policy, shows higher utilization of workstation, increased system throughput and lower levels of maintenance cost in scenarios of planned and unplanned downtime compared to the traditional preventive maintenance policy.

CHAPTER 7

CONCLUSION AND RECOMMENDATION

7.1 Conclusion

With the ever-increasing costs associated with the maintenance of industrial machinery due to downtime and machine failures, coupled with the trend of adopting just-in-time production, it has become imperative to embrace maintenance policies that promote lean manufacturing practices and eliminate waste throughout the production chain. Some of the maintenance policies currently employed by most firms include reactive and preventive maintenance, which have proven to be costly and result in various forms of waste such as loss of production time, reduced output, and frequent machinery and component failures.

However, recent advancements in artificial intelligence have led manufacturing firms to adopt a predictive maintenance approach. To make this strategy effective, firms have to determine the residual life in critical equipment in their operational machinery and simulate the manufacturing line to better predict failures and schedule maintenance based on this predictive information.

The objectives of this research were to determine the Remaining Useful Life of the rotating element thrust bearings, which simulated the manufacturing system, while conducting a comparative analysis of various maintenance strategies employed at the Holfarcam Sarl chemical plant in Cameroon.

The rotating element bearing, a critical component that significantly impacts the performance of the chemical manufacturing system, underwent an accelerated degradation test. Through experimentation, we generated the degradation profile of the bearing using a sensor-updated degradation model developed by (Gebraeel N. , 2006) and subsequently calculated the RUL. Our analysis revealed that the RUL has a numerical value of 942 hours, and the bearing had degraded by 23%. This means that the thrust bearing has a constant weight at approximately 10 KN and operated for 8 hours daily, it will experience failure after 942 hours from the time of production. With this value known, the production engineer can easily schedule maintenance, leading to reduced downtime and increased production output.

By simulating the manufacturing system, we were able to visualize the total level of degradation in the production line reliability. After simulating the manufacturing system and incorporating a failure subroutine, we observed that for every 1000 entities processed, only about 100 would be lost along the production chain. This allowed us to identify choke points responsible for the losses, notably the chemical reactor. By focusing on improving the overall performance of the chemical reactor, we can reduce losses and enhance productivity.

Furthermore, we conducted a comparative study of predictive and preventive maintenance strategies to evaluate the efficiency of the production system at various reliability percentages; 55%, 65%, 75%, 85%, and 90%, considering parameters such as frequency of failure replacement, planned replacement, total cost, workstation utilization, and workstation throughput. The following observations were made:

For the predictive maintenance policy, the frequency of failure replacement decreases from a mean of 53 to 10 as reliability decreases, while for the preventive policy, there is an increase from a mean of 89 to 672. This implies that as the reliability of the manufacturing line decreases, the frequency of parts replacement decreases with the predictive model, resulting in reduced waste.

With respect to total maintenance cost, while the predictive maintenance cost remains relatively constant with a mean amount of $1540 to $2540, the total maintenance cost for the preventive approach increases from $4250 to $10,340 as the reliability of the system decreases.

Regarding workstation utilization and throughput, the predictive maintenance policy maintains a constant mean of 90% and 12,000, respectively, for all reliabilities. In contrast, the preventive maintenance policy decreases to a mean of 40% and 5,500, respectively. This suggests that as system reliability decreases, the workstation output is significantly affected when the company employs a preventive maintenance strategy, whereas the workstation usage and output are independent of the reliability level for the predictive maintenance policy.

Based on these findings, it is reasonable to conclude this study by highlighting the fact that the research objectives were successfully achieved, and the goals set for each chapter were met. Implementing a predictive maintenance approach can significantly enhance system performance and reduce maintenance costs at the solution concentrate line of the Holfarcam Sarl chemical plant in Cameroon. This not only improves the overall efficiency of the system but also contributes to cost savings in maintenance, ultimately benefiting the operation of the plant.

7.2 Recommendation

This work was done considering critical equipment, which is the chemical reactor of the solution concentrate line whereas we had other machines in the line which could also impact productivity. Some of this machines are pumps, chillers and filling machine which takes a position in the overall performance of these system.

- A predictive maintenance simulation to determine the RUL be done for all the other machinery in the solution concentrate line such a compressor, pumps, chillers, water purifier, and filling machines.
- In the simulation study conducted for system maintenance, our models primarily utilize the normal logarithmic distribution to assess system reliability. But a Bayesian approach will be preferable in good decision making between the different maintenance strategies

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APPENDIX

A. MATLAB Code for generating Vibration Profile for the rotating Element Bearing

Show of healthy and faulty data (vibrational profile)

```
>> % load vibration data
 Load ('vibrationdata.mat');
 % create a time vector
 Fs=1000; % sampling frequency
 t = linspace(0, length(vibrationdata)/Fs,length(vibrationdata));
 % plot the vibrationdata against time
 plot (t,vibrationdata)
 xlabel('Time(s)');
 ylabel('amplitude');
 xlabel ('time(measured as 350 sec daily for 1 month)');
% Deterioration life cycle of the bearing
>> % set parameters
 alpha = 0.02; % degradation factor
 beta = 0.01; % noise factor
 t_max = 10000; % maximum time
 % compute baseline value
 y_min = min(vibrationdata);
 % set initial value
 y_0 = vibrationdata(1);
 % Initialize RUL estimate
 RUL = t_max;
 % loop over time steps
 for t = 2:length(vibrationdata)
```

```
% update RUL estimate
 for t = 2:length(vibrationdata)
for t = 2:length(vibrationdata)
RUL_new = -1/alpha *log((vibration data(t)+ beta - y_min)/(y_0 - y_min));
RUL = min(RUL, RUL_new);
% update degradation factor
alpha = (vibrationdata(t) - y_min)/(y_0 - y_min)/(exp(-alpha) + 1) + alpha * exp(-
alpha);
end
% display results
 disp(['Remaining useful life: ' num2str(RUL) 'seconds']);
Remaining useful life: 10000seconds
```

B. Remaining Useful Life Curve MATLAB Code

```
>> load('vibrationdata.mat');
% Define the threshold value and maximum lifespan
threshold = 0.1;
max_lifespan = 1000;
% Initialize the degradation level to zero
degradation_level = 0;
% Calculate the RUL for each time step using the exponential degradation model
for i = 1:length(vibrationdata)
   if degradation_level >= threshold
      % Bearing has failed
      RUL(i:end) = 0;
      break
   else
      % Calculate the RUL for this time step
      RUL(i) = max_lifespan * exp(-degradation_level);
      % Update the degradation level for the next time step
      degradation_level = degradation_level + vibrationdata (i);
   end
end
```

```
>> % Plot the RUL over time
>> plot(RUL);
xlabel('Time(days)');
ylabel('RUL(hours)');
title('Remaining Useful Life for a Rotating Element Bearing');
```

C. ARENA SIMULATION VISUAL CODES

// Arena simulation code for exponential degradation model

```
// Define the model parameters
const double INITIAL_VALUE = 100.0; // Initial value of the system state variable
const double DEGRADATION_RATE = 0.05; // Exponential degradation rate

// Create a new simulation
Simulation simulation;

// Create a new entity type
EntityType entityType;
entityType.Name = "Entity";

// Define the entity attributes
entityType.Attributes.Add(new Attribute("State", INITIAL_VALUE));

// Create a new process
Process process;
process.Name = "Process";

// Add a create module to the process
CreateModule createModule;
createModule.Name = "Create";
createModule.EntityType = entityType;
createModule.Interval = 1.0; // Create an entity every 1 time unit
process.AddModule(createModule);

// Add a delay module to the process
DelayModule delayModule;
delayModule.Name = "Delay";
delayModule.Mean = 1.0; // Delay each entity for 1 time unit
process.AddModule(delayModule);

// Add an assign module to the process
AssignModule assignModule;
assignModule.Name = "Assign";
assignModule.Expressions.Add(new Expression("State", "State * exp(-
DEGRADATION_RATE * Delay)"));
```

```
process.AddModule(assignModule);

// Add a dispose module to the process
DisposeModule disposeModule;
disposeModule.Name = "Dispose";
process.AddModule(disposeModule);

// Add the process to the simulation
simulation.AddProcess(process);

// Run the simulation
simulation.Run(1000); // Run the simulation for 1000 time units

// Collect the simulation results
List<double> stateValues = new List<double>();
foreach (Entity entity in simulation.Entities)
{stateValues.Add(entity.Attributes["State"].Value);}

// Analyze the simulation results
```

// Arena simulation code for resource failure subroutine

// Define the subroutine parameters const double PROBABILITY_OF_FAILURE = 0.1; // Probability of resource failure per time unit const double REPAIR_TIME = 10.0; // Time to repair the resource

// Create a new subroutine Subroutine subroutine; subroutine.Name = "ResourceFailure";

// Add a create module to the subroutine CreateModule createModule; createModule.Name = "Create"; createModule.EntityType = "ResourceFailure"; createModule.Interval = PROBABILITY_OF_FAILURE; // Create a resource failure entity every 1 / PROBABILITY_OF_FAILURE time units subroutine.AddModule(createModule);

// Add a delay module to the subroutine DelayModule delayModule; delayModule.Name = "Delay"; delayModule.Mean = REPAIR_TIME; // Delay each resource failure entity for REPAIR_TIME time units subroutine.AddModule(delayModule);

// Add a dispose module to the subroutine DisposeModule disposeModule; disposeModule.Name = "Dispose"; subroutine.AddModule(disposeModule);

// Create a new entity type for resource failures EntityType resourceFailureEntityType; resourceFailureEntityType.Name = "ResourceFailure";

// Define the entity attributes resourceFailureEntityType.Attributes.Add(new Attribute("Resource", ""));

// Add the resource failure subroutine to the simulation Simulation simulation; simulation.AddSubroutine(subroutine);

// Create a new process that uses the resource Process process; process.Name = "Process";

// Add a seize module to the process SeizeModule seizeModule; seizeModule.Name = "Seize Resource"; seizeModule.Resource = "Resource"; process.AddModule(seizeModule);

// Add a delay module to the process DelayModule delayModule; delayModule.Name = "Process Task"; delayModule.Mean = 1.0; // Process the task for 1 time unit process.AddModule(delayModule);

// Add a release module to the process ReleaseModule releaseModule; releaseModule.Name = "Release Resource"; releaseModule.Resource = "Resource"; process.AddModule(releaseModule);

// Add the process to the simulation simulation.AddProcess(process);

// Run the simulation simulation.Run(1000); // Run the simulation for 1000 time units

// Collect the simulation results // ...

// Arena simulation code for reliability of series-parallel configuration of processes

// Define the model parameters const int

NUM_PROCESSES_IN_SERIES = 2; // Number of processes in the series group const int

NUM_PROCESSES_IN_PARALLEL = 3; // Number of processes in the parallel group const double

RELIABILITY_OF_PROCESS = 0.9; // Reliability of each individual process

// Create a new simulation Simulation simulation;

// Create a new entity type EntityType entityType; entityType.Name = "Entity";

// Define the entity attributes entityType.Attributes.Add(new Attribute("State", 1.0)); // State of the system (1.0 = working, 0.0 = failed)

// Create a new process for the series group Process seriesProcess; seriesProcess.Name = "Series Process";

// Add a create module to the series process CreateModule createModule; createModule.Name = "Create"; createModule.EntityType = entityType; createModule.Interval = 1.0; // Create an entity every 1 time unit seriesProcess.AddModule(createModule);

// Add a delay module to the series process DelayModule delayModule; delayModule.Name = "Delay"; delayModule.Mean = 1.0; // Delay each entity for 1 time unit seriesProcess.AddModule(delayModule);

// Add an assign module to the series process AssignModule assignModule; assignModule.Name = "Assign"; assignModule.Expressions.Add(new Expression("State", "State * RELIABILITY_OF_PROCESS")); seriesProcess.AddModule(assignModule);

// Add a dispose module to the series process DisposeModule disposeModule; disposeModule.Name = "Dispose"; seriesProcess.AddModule(disposeModule);

// Create a new process for the parallel group Process parallelProcess; parallelProcess.Name = "Parallel Process";

// Add a create module to the parallel process CreateModule createModule; createModule.Name = "Create"; createModule.EntityType = entityType; createModule.Interval = 1.0; // Create an entity every 1 time unit parallelProcess.AddModule(createModule);

// Add a delay module to the parallel process DelayModule delayModule; delayModule.Name = "Delay"; delayModule.Mean = 1.0; // Delay each entity for 1 time unit parallelProcess.AddModule(delayModule);

// Add an assign module to the parallel process AssignModule assignModule; assignModule.Name = "Assign"; assignModule.Expressions.Add(new Expression("State", "State * RELIABILITY_OF_PROCESS")); parallelProcess.AddModule(assignModule);

// Add a dispose module to the parallel process DisposeModule disposeModule; disposeModule.Name = "Dispose"; parallelProcess.AddModule(disposeModule);

// Add the series and parallel processes to the simulation simulation.AddProcess(seriesProcess); simulation.AddProcess(parallelProcess);

// Connect the series and parallel processes seriesProcess.Output.ConnectTo(parallelProcess.Input);

// Run the simulation simulation.Run(1000);

// Run the simulation for 1000 time units:

// Collect the simulation results List<double> stateValues = new List<double>(); foreach (Entity entity in simulation.Entities) { stateValues.Add(entity.Attributes["State"].Value);}

CURRICULUM VITAE