STATISTICAL MODELING AND ANALYSIS OF EQUIPMENT MAINTENANCE TIME IN THE PROCESSING INDUSTRY: A CASE STUDY OF RIVATEX EAST AFRICA LIMITED

BY

BETT BRIAN KIPCHUMBA

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN INDUSTRIAL ENGINEERING, DEPARTMENT OF MANUFACTURING, INDUSTRIAL AND TEXTILE ENGINEERING, SCHOOL OF ENGINEERING

MOI UNIVERSITY

2023

DECLARATION

Declaration by students

This thesis research represents my original work and has not been submitted for a Master's degree or any other degree at any other university. The entirety of this research, including its constituent parts, may not be reproduced without the explicit written consent of both the author and Moi University.

Signature: …………………………… **Date: …16/…07…/…2023.**

Bett Brian Kipchumba **TEC/PGMT/04/18**

Declaration by Supervisors

This thesis has been submitted for examination with our approval as University Supervisors.

Dr. Peter Chemweno

…………………………………. **Date: …14/…07…/…2023….**

Dr. Jerry Ochola

…………………………………. **Date: …17/…07…/…2023….**

Dr. Eric Oyondi

…………………………………. **Date: …17/…07…/…2023….**

PREFACE

This thesis is unpublished, original, and independent work by the author.

PUBLICATION

Bett Kipchumba, Peter Chemweno, Eric Nganyi, Jerry Ochola. Statistical mapping of the critical equipment and data collection on the number and time between failures encountered in the weaving section of the textile manufacturing processes. Engineering reports. 2023. DOI: 10.22541/au.168120553.35939250/v1

ACKNOWLEDGMENT

This work would not have been possible without the unwavering support of my parents, family, wife, and children. Truly, they have been my pillars of strength, standing beside me in every pursuit and playing a crucial role in the success of this research. I am deeply grateful for their unwavering love and encouragement. I would like to express my heartfelt thanks to my parents and family for their continuous support and belief in my abilities. Their unwavering support has been a constant source of motivation throughout this journey. In addition, I am incredibly grateful for the immense support and understanding shown by my wife and children. Their patience, understanding, and unwavering belief in me have been instrumental in the completion of this thesis. I am truly blessed to have them by my side. I would also like to acknowledge the invaluable contributions and guidance of my supervisors, the dedicated employees of Rivatex East Africa Limited (REAL), and the esteemed faculty members of Moi University's Manufacturing, Industrial, and Textile department. Their support has been instrumental in shaping the outcome of this research. Furthermore, I would like to express my gratitude to my colleagues for their assistance during challenging moments encountered while writing this thesis. Their help in overcoming difficulties has been greatly appreciated.

ABSTRACT

Unexpected equipment failure in machines interrupts production schedules and creates costly downtime. Therefore, the importance of timely equipment maintenance is to extend the machine lifespan, prevent unplanned downtime, and reduce the need to buy equipment. Rivatex East Africa Limited (REAL) has an overcapacity of looms with inconsistent maintenance time schedules. The main objective of the research was to establish a suitable maintenance schedule time and parameters by assessing the state of maintenance practices of the critical equipment in the weaving section at REAL. The specific objectives were to map out the critical equipment in the weaving section, to model the time between maintenance operations and the number of failures and lastly, to synthesize the system data to establish an optimized maintenance schedule and parameters. The maintenance time schedules of rapier, and air-jet looms at REAL were studied. Data collections were by real-time observations, questionnaires, and interviews administered to 20 personnel using a simple random sampling method suitable for a small population. Semi-structured interviews had both predetermined and unplanned questions whereas both open and closed ended questionnaire were used. Failure mode and effect analysis, fishbone diagram, Weibull distribution, and Monte Carlo simulation were undertaken followed by regression analysis of the data. The setup of the Monte Carlo simulation entailed 1000 instances of the random values from the systems in the critical equipment. The data were optimized through Monte Carlos regression modeling and Weibull distribution analysis to get shape parameter and the scale parameter of 1.47 and 1683.46 hours. Regression analysis indicated that 95.50% of the variation in mean time between failures was due to total time and the number of failure variables in critical equipment systems. A preliminary survey on downtime indicated up to 60 days, the productivity was estimated at 194.76 meters, and efficiency was 90%. In conclusion, the findings indicated that weaving looms were the critical equipment. The model's shape parameter of 1.47 described a steady increase in the risk of wear-out failure during the early life of the machines. Also, the value of the shape parameter suggested early wear-out failure and premature failures after installation. The optimal time interval for maintenance operations was 1683.46 hours from the scale parameter. The findings indicated that REAL's looms had an inconsistent and incoherent maintenance time scheduling approach. According to the results, it is recommended that preventive maintenance schedules be done once every 1683.46 hours. Further research is recommended to investigate non-maintenance management strategy aspects of scheduling maintenance activities for industrial equipment, including unplanned/reactive maintenance, preventive maintenance, and predictive monitoring.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE: INTRODUCTION

This chapter provides the background of the research, statement of the problem, justification of the research, objectives, research question, the theoretical framework, scope of the research, and the methods. Furthermore, this chapter provides the significance of the study with the aim of developing the picture scenario.

1.1 Background

Maintenance forms a crucial part of any manufacturing process that involves the use of machines. In essence, certain elements of competitiveness, such as the desire for quality, product lead time, and cost, play a major role in optimized maintenance strategies. In textile mills, there is frequently a considerable emphasis on maintenance in order to meet a variety of critical goals. Minimizing rework, saving production costs, boosting machine precision, increasing product homogeneity, and shortening lead times are all examples. Textile factories can increase their overall efficiency and output by prioritizing maintenance in these ways. Effective maintenance can aid in the prevention of costly and time-consuming errors, the reduction of waste and rework, and the optimization of machine performance. As a result, the textile factory's customer happiness, competitiveness, and profitability can all improve. A combination of long uptime of the machine and quality compliant products enables the textile mills to cut the production cost. Therefore, statistical modeling using regression is used to assess machine reliability and availability to model a robust maintenance strategy with significant and competitive factors of maintenance (Shafiee & Sorensen, 2019). All these are tailored in a manner that the maintenance strategy at Rivatex East Africa Limited (REAL) is visualized and the problem at hand elaborated for the purpose of the study.

Furthermore, maintenance is a combination of administrative and technical actions that are intended to resort of maintain the condition of the system in a state that functions normally (ISO 14224: 2004). In this case, it was evident that the machine must be available in the entire production or service time. The cost of maintenance can be a significant proportion of the total production cost for a company, ranging from 15% to 70% (Ilangkumaran et al., 2009). To reduce this cost and increase the reliability and availability of machines, statistical modeling such as regression analysis can be used to identify a suitable maintenance strategy that minimizes planned, short, and unplanned stoppages (Ilangkumaran et al., 2009). The cost of maintenance can be high due to the high cost of restoring the equipment, safety hazards caused, and, secondly, damages associated with failures. Studies in India show that 50 % of textile companies fall under the medium level maintenance while only 10% give high-level maintenance strategies[CITATION Ami14 \l 1033]. In essence, a high level has a suitable maintenance strategy and has effective use of the resources. In medium and low-level maintenance, the suitability of the strategy and the utilization of the resources are poor. Similarly, reducing the probability of failure based on preventive maintenance translate to 12% to 18% savings in the cost of production (TT, 2018).

REAL is a manufacturing industry with processes such as spinning, weaving, dyeing, printing, garments finishing, and garment manufacture. All these processes form the production line, each with a production target. However, the targets are not met due to inconsistencies in the maintenance processes and schedules. A production line requires that all the machines should be operating without breakdown that might require a halt of the entire production line. Based on this need, the aspect of reliability, maintainability, and operability of the machines becomes a necessity in the production line. The purpose of performing maintenance is to increase the life of the machine. In other words, the meantime to the next failure of the machine failure is extended. A better maintenance strategy can reduce machine downtime interruption, hence a factor in the reliability of the machines. Therefore, a study to investigate existing maintenance practices at REAL, with a view of statistically modeling and analyzing equipment maintenance time. The reliability of the machines in a production line is often paramount in the productivity of a facility, especially when proper maintenance strategies are used to enhance production [CITATION BPM15 \l 1033]. A proper maintenance strategy can cut the maintenance costs by 80% and further reduce the losses in production (Chan & Mo, 2017). REAL has a weaving section that largely depends on breakdown maintenance strategy and schedules with little commitment to preventive maintenance scheduling. Some of the planned preventive maintenance schedules in the weaving section are overlooked, with much attention being paid to the lubrication and dusting off the machines (Mahlangu & Kruger, 2015).

1.2 The Problem Statement

REAL's maintenance strategy is characterized by both the breakdown maintenance (run to failure maintenance) strategy and preventive maintenance. In most maintenance cases, the machine operator waits until the machine fails in order to repair it. As much as dusting is done and lubrication, there is little commitment to clearing the fibers that build upon the oiled section prior to the running of the equipment. The approach used has disadvantages since it requires more than two machines in order to maintain production when one is redundant. The facility views equipment breakdown as either an emergency or breakdown maintenance. The machines are maintained based on the preventive maintenance strategy. For instance, inspection, cleaning, greasing, retightening, and oiling dominate the maintenance activities as they tasked personnel awaits the breakdown of the machine. A preliminary survey on the critical equipment shows the effectiveness of current strategies in terms of availability, 21% of the machines are available throughout the shift without stoppages. Also, downtime ranges from 10 minutes to 24 hours. Other machines can stop working for up to 60 days. The time needed to scan for failure ranges from 10 to 30 minutes. The target efficiency and production are 90% and 194.76 m, respectively, which point to a gap that needs to be addressed through the adoption of consistent and proper maintenance time schedules. Weaving equipment forms a critical section due to dominant cases of breakdown maintenance (Run to failure maintenance) and inconsistencies in the preventive maintenance strategies. The critical equipment in the weaving section lacked a clear maintenance program and relied on the experience of the maintenance crew as opposed to the original equipment manufacturer (OEM). A preliminary survey on failure, downtime, availability, productivity, and efficiency reveals that the scheduling of machine maintenance is not coherent. The data points at the need for a robust maintenance time scheduling program, an effective failure analysis, and a more appropriate approach to maintenance. The weaving department is critical in that product from the spinning department must pass through in order to reach the processing department.

1.3 Justifications of the Research

The research is based on the situation analysis of a weaving section of a textile mill with the aim of establishing the need for a consistent and coherent maintenance time scheduling strategy. There are discrepancies and inconsistencies in the maintenance of critical equipment that suggests that the existing strategy is not optimized and does not guarantee machine availability. The rationale implies that critical equipment needs optimized maintenance time schedules. From the background information and the statement of the problem, the cases of Run failure maintenance and prolonged downtimes of up to 60 days led to compromised availability of machines. Run to failure system of maintenance approach does not guarantee the efficiency of the machine and can be associated with an increased cost of maintenance and replacement. Therefore, this study shows some of the grounds to affirm the need for an effective maintenance time scheduling strategy in a fabric manufacturing factory.

1.4 Objectives

1.4.1 General Objective

To establish a suitable maintenance schedule time and parameters by assessing the state of maintenance practices of the critical equipment in the weaving section at REAL.

1.4.1 Specific Objectives

i. To map out the critical equipment and collect data on the number and time between failures encountered in the weaving section of the textile manufacturing processes.

ii. To model the time between maintenance operations and the number of failures in system components within the duration for the critical equipment.

iii. To analyze the system data to establish an optimized maintenance schedule and parameters for the critical equipment for the time between maintenance operations.

1.4 Scope of the Research

The research is based on the critical equipment that is found within the weaving section of REAL. The critical equipment as identified in the background information and the problems statement is the rapier and the air-jet looms. Based on the situational analysis, there are discrepancies that suggest that the existing maintenance strategy that is not optimized and does not guarantee optimum machine availability. Such discrepancies and inconsistencies provide evidence of the gap and the need to undertake a study to resolve the underlying problem.

1.5 Significance of the study

The research played an important role in assessing the current situation concerning the maintenance strategy at REAL with the aim of statistically modeling a maintenance time schedules that presents an optimized strategy. The critical machines were evaluated, the problem of inconsistency and lack of coherent maintenance time scheduling strategy was established, and a solution was developed. Furthermore, the research provides a recommendation to REAL on how to go about the process of maintenance. The significance of the research is to help resolve the problem faced as far as machine maintenance is concerned. The study ensured that the machine availability was prolonged by pointing out the gap in the maintenance strategy used and ensuring that an optimized time is established based on the failure scenario deduced from Weibull distributional analysis.

1. 6 Outline of the Thesis

The thesis comprises five chapters: Chapter One introduces the study, Chapter Two provides a comprehensive literature review, Chapter Three outlines the methodology employed, Chapter Four presents the results and discussions, and Chapter Five concludes with recommendations. The references and appendices are also included.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of the literature review that helps in depicting the gap in the case of Rivatex East Africa Limited (REAL). Maintenance can be termed as an approach that involves a combination of strategies and techniques in order to avoid the occurrence of failure and tactfully restore failed components. In the past, maintenance has been about cost and the nature of stoppages encountered during the production process. However, the current system evaluates maintenance in terms of reliability, downtime, safety, and availability of the machines. The traditional approaches have been replaced by more advanced maintenance strategies. In essence, the optimization of maintenance schedules has been a pressing challenge, and most industries have striven to find ways of minimizing downtime. In order to minimize downtime, there is a need to find ways to maximize machine availability by enhancing the reliability and uptime of the machines. Proactive strategies such as predictive and preventive maintenance have been instrumental in the maximization of machine availability (Mahfoud et al., 2016).

2.1.1 Rivatex East Africa Limited

Rivatex East Africa Limited (REAL) is a vertically integrated textile factory that converts cotton lint through various processes to finished fabrics. The principal goal of REAL, a business wholly owned by Moi University, which was established on August 16, 2007, was to use the facility for training, research, extension, and commercial uses. REAL is reputed as the home of quality textile products both locally and regionally. In addition, the company has been facing a problem of obsolete machinery and technology challenges which has hindered the exploitation of the opportunities that exist in the local and regional markets. Among these challenges is the issue of machine maintenance amid the issue of machine obsolescence. Lastly, the company has made various steps towards full revival despite the many challenges that it has faced on its way towards sustainable growth and profitability.

REAL has three weaving technologies in the weaving department, namely projectile, rapier, and air jet. Under rapier weaving technology, there is a dobby and tappet mechanism. Dobby loom refers to a loom that controls all the warp yarns using a dobby system. Tappets imply a shedding mechanism by a loom using a tool placed on the peak of the loom in order to develop patterns using a limited number of healds created by the tappet and cam motion.

2.1.2 REAL Manufacturing processes

The steps for the manufacturing process are as shown in Figure 2.1.

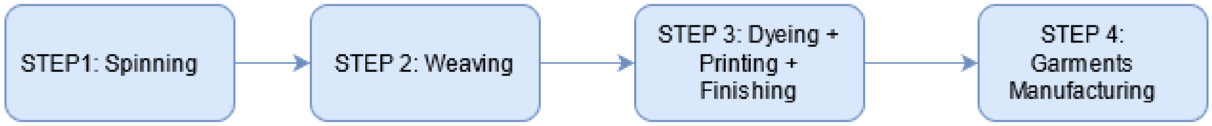


Figure 2.1: Textile Manufacturing Process with Flow chart (Uddin, 2019)

Spinning is a process used to create or transform fiber materials into yarns (Mahmood, 2020). It first passes through the blow chamber, where the size of the cotton is reduced with the use of machines, then it is carded (Uddin, 2019). Drawing is used to carry on the process after carding, which involves attenuating in spinning mills as shown in Figure 2.1. Following drawing, the sliver is processed for combining, where the cloth's uniform size is achieved. According to Scime et al. (2020), the process is then advanced for roaming in order to prepare the input package. Shirvanimoghaddam et al. (2020) argues that rollers attenuate this roving before it is spun around the spindle. The next step following spinning is the weaving process. In this location, the spun yarn is delivered for additional doubling and twisting. After that, it goes through processing so that the yarn can be moved in a handy box with enough yarn length. The worn-out packages are swapped out for new ones at the creeling stage, and then warping occurs (Uddin, 2019). Sizing is the protective layer that is applied to the bent yarn to reduce yarn breaking. According to Huynh (2020), sizing is regarded as a crucial section. He et al. (2020) argued that the final stage of weaving supports the processing of this yarn for winding on the weaver's beam. A fabric is the result of this stage.

A loom also known as Weaving Machine refers to a tool used for weaving yarn and thread into textiles, or a cloth as shown in Figure 2.1. In the first half of the '70s, there was an arrival in the market of systems used in weft insertion other ways than the shuttle (Uddin, 2019). Machines with mechanical weft include insertion systems by rigid rapiers, flexible rapiers, and projectiles. On the other hand, machines with non-mechanical weft means of insertion system include jets of compressed air and jets of compressed water. REAL employs the use of weaving machines that inserts weft by rigid rapiers, projectile, and the jet of compressed air (Islam et al., 2021). There are a total of 88 weaving machines using these 3 mentioned insertion systems and fall under the critical equipment as per the initial assessment.

In dyeing mills, the process of dying and printing cloth normally comes before adding additional finishing touches. Dyeing gives fabric color and enhances its appearance. The process of finishing involves changing the product from woven to knitted fabric. To produce a specific aesthetic, finishing is specifically done after dying or printing. Manufacturing clothing is the final step in turning semi-finished fabric into completed fabric.

To produce cloth, garment manufacturing companies go through several procedures. Designing, Sampling, Costing, Maker Making, Cutting, Sewing, Washing, Finishing, Packing, Final Inspection, Dispatch, and many other operations are included in this section of textile manufacturing (Uddin, 2019). A textile factory consists of interdependent series of machines; therefore, the maintenance theory of reliability becomes relevant in that the entire machine must be kept running. Uddin (2019) affirms that the need to avoid failure and breakdown emergencies hinders the aspect of reliability and availability of the machines. Failure and defects are viewed as discrete events that are in a queue. Furthermore, there are events that are characterized by failure modes, schedules, and the need for reaction. According to Andrade et al., (2020), such a scenario dictates the conceptual framework required to assess the situation at REAL. The availability and reliability of machines calls for a change in the maintenance strategy. In essence, the maintenance theory of reliability sort to assess the usefulness and the practical maintenance models associated with inspection, prevention, and replacement of machines systems (Nakagawa, 2006). Uddin (2019) argues further that the availability of the machines can be narrowed down to the theorem that the maintenance cost of the machine increases with time until a point is reached when it is no longer economical to run the machines, hence affecting its availability. Finally, the theory of probability becomes crucial in the assessment of the efficiency, reliability, and availability of the machines since it is simpler to guest the eventuality of a chance for failure at various operational stages (Mehta et al., 2015).

2.1.3 Common textile manufacturing processes maintenance issues

Textile manufacturing processes entail a wide range of gear and equipment, each with its own set of maintenance issues. Spinning machines are used to turn fibers into yarn. The continual friction between the fibers and the machine's parts causes wear and tear on these machines. Wear and tear can reduce efficiency and potentially cause machine failure. Jia et al. (2020) explains that to avoid this, the machine must be lubricated and cleaned on a regular basis to reduce friction and remove any dirt that has accumulated. Sarı et al. (2020) found out that replacing worn-out parts like bearings, spindles, and rollers can help assure the machine's best operation. The fundamental issue with spinning machines is frictional wear and tear on the parts. Wear and tear on the machine might cause it to slow down, create subpar yarn, or even stop working entirely. These issues can be avoided by regular lubrication, cleaning, and replacement of worn-out parts. Liu et al. (2020) states that weaving machines are susceptible to vibration and shock, which can cause bolts and nuts to loosen, resulting in part misalignment. Regular maintenance, such as checking the tightness of bolts and nuts, replacing worn-out parts, and properly aligning parts, can help prevent these issues. Fabric is created by interlacing strands on weaving machines. These machines are susceptible to vibration and shock, which can cause bolts and nuts to loosen, resulting in component misalignment. Islam et al. (2021) stated that misalignment might cause the machine to generate poor quality fabric or possibly stop working entirely. Regular maintenance to check the tightness of bolts and nuts is required to prevent this occurrence. Furthermore, replacing worn-out elements like drive belts, bearings, and shafts can assist assure the machine's peak functioning. Weaving machines are susceptible to vibration and shock, which can cause bolts and nuts to loosen, resulting in part misalignment. Prasad et al. (2020) stated that regular maintenance, such as checking the tightness of bolts and nuts, replacing worn-out parts, and properly aligning parts, can help prevent these issues. Because of the acidic nature of the dyeing process, dyeing machines corrode. To dye fabric or yarn, dyeing machines are employed. Because of the acidic nature of the dyeing process, these machines are prone to corrosion. Corrosion can cause leaks, corrosion, and structural damage to the machine, resulting in lower efficiency and possibly machine failure. According to Pal (2020), to avoid corrosion, the machine must be cleaned on a regular basis to remove any remaining colour or debris that has accumulated. Furthermore, treating the machine's surfaces with protective materials such as paint or anti-corrosion coatings can aid in corrosion prevention. Printing machines are used to transfer designs or patterns from paper or fabric to fabric. According to Realyvásquez et al. (2020), this is because of the abrasive nature of the printing process; these machines are prone to wear and tear. Wear and tear can cause the machine's parts to break, resulting in poor print quality or machine failure. To avoid wear and tear, the machine must be cleaned on a regular basis to remove any residual ink or dirt that has accumulated. Furthermore, replacing worn-out elements including ink rollers, ink cartridges, and print heads can assist assure the machine reach peak performance. Corrosion can cause leaks, corrosion, and structural damage to the machine, resulting in lower efficiency and possibly machine failure. Regular cleaning and protective coating of the machine's surfaces can assist prevent these issues. Mahmood (2020) argues that because of the abrasive nature of the printing process, printing machines are vulnerable to wear and tear. This wear and strain might cause the machine's parts to break, resulting in poor print quality or machine failure. Cleaning and replacing worn-out parts on a regular basis can help prevent these issues. Due to the repeated cutting of fabric, cutting machines' blades become dull. Fabric and paper cutting machines are used to cut fabric and paper into precise shapes and sizes. Holgado et al. (2020) claims that this dullness is due to the repeated cutting of fabric, the blades on these machines become dull. Blades that are dull can cause inconsistent cuts, ragged edges, and decreased efficiency. To avoid the decreased efficiency, blades must be sharpened or replaced on a regular basis. Additionally, cleaning the machine to eliminate any accumulated material can help assure the unit's best operation. Blades that are dull can cause inconsistent cuts, ragged edges, and decreased efficiency. Sharpening or replacing blades on a regular basis can help prevent these issues of decreased efficiency. According to Parvin et al. (2020), to prevent issues of decreased efficiency in textile production operations, constant maintenance, cleaning, and replacement of worn-out parts are required. It is also critical to follow the manufacturer's instructions for optimal equipment use and maintenance.

Weaving machines are key equipment in textile manufacturing processes and must be serviced on a regular basis to ensure peak performance. The warp is a collection of strands that run longitudinally on a weaving machine. If the warp breaks, the machine will stop running, resulting in production downtime and lower efficiency. Warp breaks are most commonly caused by improper tension, worn-out or damaged warp beams, or faults in the warp yarn. These shortcomings of improper tension can be avoided by performing regular maintenance on the warp beams, tensioning systems, and yarn feeders. The weft is a group of strands that run across the weaving machine. Fithri et al. (2020) argues that whenever the weft strands become trapped or jammed, the machine ceases operating, resulting in production downtime and lower efficiency. Weft jamming is most commonly caused by improper tension, a damaged or worn-out shuttle or rapier, or faults in the weft yarn. Maintenance of the shuttle or rapier, tensioning mechanisms, and yarn feeders on a regular basis can help prevent these issues. The reed is a comb-like device that aids in the beating of the weft strands during the weaving process. If the reed is not properly oriented, the weft threads may be wrongly placed, resulting in poor fabric quality. Misalignment can be caused by worn or damaged reeds, poor tensioning of the warp and weft yarns, or structural flaws in the machine. Regular reed, tensioning device, and machine structural maintenance can help prevent these issues. Modern weaving machines frequently feature intricate electronic control systems that, if not properly maintained, can fail. Failure of these systems can cause the machine to stop running or generate poor quality cloth. Electrical shorts, broken sensors, and faulty controllers are common causes of electronic control system failure. Saggiomo et al. (2020), found out that regular maintenance of the electronic control system, including sensor and controller cleaning and inspection, can assist prevent these shortcomings. In conclusion, weaving machines are prone to a variety of malfunctions that might result in production downtime and lower efficiency. McLaren et al. (2020) further suggest that regular maintenance, which includes inspection, lubrication, cleaning, and the replacement of worn-out parts, can help prevent these shortcomings and assure peak performance. Proper machine operator training and attention to manufacturer's instructions can also aid in the prevention of problems and the extension of the machine's lifespan.

2.2 Maintenance Strategies

Textile factories are normally faced with different failures that call for decision-making approaches that are tailored towards addressing the maintenance problem. Under this heading, it is important to review the maintenance strategies that suitably match the maintenance requirements of a textile mill such as REAL.

Maintenance is done in order to maintain the machines running normally without downtime (Endrenyi, et al., 2001). Therefore, the useful life period of the machine is lengthened by reducing the component failure rate. The efficiency and availability of such a machine are achieved by ensuring that a proper maintenance strategy is adopted (Gupta & Gupta, 2020). However, the development of a maintenance strategy happens to be a challenging and complex undertaking considering the case of textile firms, and especially firms in developing countries such as REAL. The complexity of developing a maintenance strategy stems from the two approaches of measuring equipment or process performance. These two approaches include the scheduled and the actual measures. Scheduling defines the strategy to use and the sequence of evidence (TT, 2018). Similarly, the actual measure outlines the process performance during and after the maintenance has been undertaken. In the actual output, the true performance of the machine was assessed and includes the reworks and unscheduled and scheduled downtime. The unscheduled downtime may originate from equipment breakdown due to application of sub-optimal maintenance strategies (Endrenyi, et al., 2001). On the other hand, the scheduled equipment output refers to the performance of the machines over time, given the optimum allocation of work and production resources.

Furthermore, regression modeling helps in formulating appropriate maintenance strategies for optimizing machine uptime, an aspect which was complex considering many factors such as machine availability, reliability, operation patterns of equipment, among many other factors (Endrenyi, et al., 2001). Universally, maintenance affects the system and component reliability. Therefore, if little or no effort was made in the process of maintaining the machines, costly failure may occur, and finally, the aspect of efficiency is lost. Endrenyi, et al. (2001) explained that whenever maintenance is done often, efficiency tends to improve, and the maintenance cost increases drastically. Likewise, whenever an optimized maintenance strategy is employed, it implies that there is a satisfactory system and component efficiency (Endrenyi, et al., 2001). Furthermore, the system capacity has more reliable components, and reinforced redundancies are often viewed in advanced maintenance strategies.

2.2.1 Preventive Maintenance

Preventive maintenance (PM) refers to a maintenance strategy that is performed on a machine in order to prevent it from failing. In essence, the practice is aimed at increasing the productive life of a machine. The practice is undertaken when the machine is still in operation in order to avoid unexpected breakdown[CITATION HMa16 \l 2057]. The maintenance activity schedule of done based on certain triggers that suggest the need for maintenance. PM is quite complex and requires knowledge about the machine, unlike the Run to failure technique. Mahfoud et al. (2016) argues that the technique is quite useful when there is a likelihood of failure. Also, the technique works best when the failure modes can be prevented. Most importantly, the role and function of the machine must be critical in the production line. Some advantages of this method are as follow[CITATION HMa16 \l 2057],

- Equipment is kept running for longer than any other maintenance strategy.
- Lower cost of long-term maintenance of the machine.
- Safety is improved, and the operator remains safe from catastrophic failures.

The method, however, has demerits such as;

- More complex to plan than other strategies.
- The initial cost of investment is high.
- Application in textile mills.

The application of preventive maintenance in textile mills has been done based especially when the equipment is critical to the productivity of the facility. In this case, PM is considered as a planned maintenance strategy. Mahfoud et al. (2016) argues that the operations that are evaluated in preventive maintenance strategy include cleaning, setting, and minor repairs. Lubrication is a common example of the PM strategy in a textile factory [CITATION HMa16 \l 2057].

2.2.2 Predictive Maintenance

Predictive maintenance (PdM) refers to the strategy that relies on the prediction of the failures of a machine. When the time of occurrence of the failure has been determined, the maintenance team is dispatched to attend the machining order to avoid the occurrence of the failure[CITATION Ber16 \l 2057]. Monitoring of such failures helps the craftsmen to be planned and make necessary inventory requirements on time. The method helps in avoiding unplanned reactive maintenance and the extra cost that is incurred in preventive maintenance. Techniques such as observation of the vibrations, thermal imaging, and oil analysis, among others, can help in predicting failures. The methods are associated with advantages such as minimizing maintenance time, minimizing production hours lost during maintenance, and minimizing the cost of unnecessary purchase of spare parts. The merits of using predictive maintenance are (Schmidt et al, 2016);

- The cost and the time of maintenance are normally kept low.
- Reliability is improved, and the likelihood of failure is reduced significantly.

On the other hand, predictive maintenance has limitations such as;

- Higher planning and anticipation cost than basic maintenance practices.
- Application in textile mills.

PdM has been adopted in textile mills mainly in the prediction of the failures, which would eventually save on the cost of maintenance, in this case, the settings, adjustments, cleaning, and minor repairs done regularly. Schmidt et al. (2016) found out that checking forms the basis of this maintenance strategy within a facility. PdM is done, for instance, on the epicyclical gearings, rollers, V-belt, and V-pulley [CITATION Ber16 \l 2057].

2.2.3 Run to Failure Maintenance

Run-to-failure maintenance, also known as breakdown maintenance is normally associated with machines that are not critical in the production processes. Such machines are characterized by the low cost of maintenance. Similarly, the impact of such machines during downtime is insignificant. In a textile mill, the machines are normally fixed by repair, part replacement, or restoration. In this case, the maintenance is based on breakdown until it becomes feasible to order replacement equipment. The advantages of this method are [CITATION Ber16 \l 2057];

- Minimum or no planning at all is needed.
- The sequence of events and processes is simple to understand.
- On day by day, less work is done hence less staff is needed.

The disadvantages of Run to failure (Breakdown) maintenance are [CITATION Ber16 \l 2057];

- Failure is normally unpredictable.
- Normally is extremely costly and time-consuming.
- Poses a high risk to the machine operators.

In the textile manufacturing system, run to failure maintenance is also often applied, in the sense that textile mills often consider this strategy when the equipment is not critical to the production processes. Operations such as repairing, altering, setting, adjustment, and overhauls are normally undertaken under breakdown maintenance. In essence, most of the operations done in this strategy are normally not scheduled. Schmidt et al. (2016) researched that overhauling maintenance is undertaken when the machine suddenly stops or reaches the manufacturer's recommendation or when most of the parts have worn out.

A run to failure approach to the maintenance of the machine is characterized by secondary damage complications. In most cases, the secondary damages often result from primary damages asset failures that have been overlooked for a long time. Safety and security issues tend to increase with prolonged uses of machines in the case of run to failure approach [CITATION Ber16 \l 2057]. Alongside the safety concerns, the approach is associated with low user comfort and satisfaction levels.

2.2.4 Condition-based maintenance

Condition-based maintenance (CBM) is a maintenance strategy that involves routine testing, visual inspections, and sensor devices to monitor equipment performance and predict when repair will be carried out most affordably. CBM is a strategy where the primary driver behind performing maintenance is a change in the condition or performance of the equipment (Wu et al., 2019). The asset, a component of it, or a part of it is actually monitored to identify when is the best time to undertake maintenance (Wu et al., 2019). By gathering and analyzing sporadic or continuous data about the operational state of crucial assets' components, CBM aims to reduce the overall cost of inspection and repairs as shown in Figure 2.2. On-condition maintenance is often used to detect the onset of failures and recommended maintenance practices.

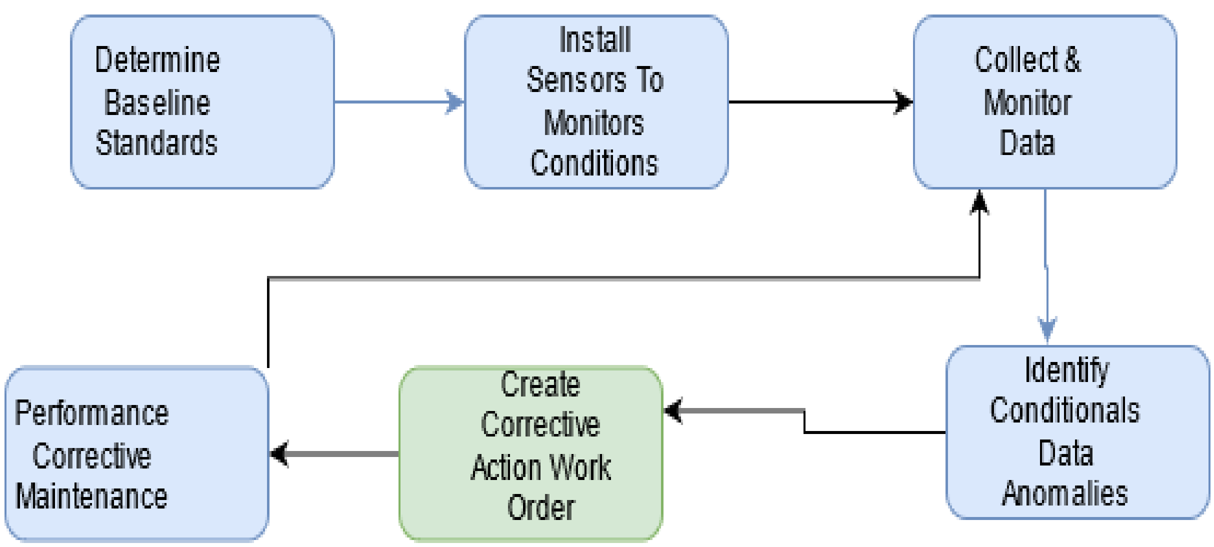


Figure 2.2: Condition-Based Maintenance Workflow (Nguyen et al., 2019)

The differences between CBM and PdM are quite outstanding and needs to be explored as shown in the comparison Table 2.1 (Wu et al., 2019);

Table 2.1: CBM versus PdM

Condition-Based Maintenance	**Predictive Maintenance**
Relies on condition-based diagnostics to determine when maintenance is necessary (For example: vibrations, temperature, pressure, speed, voltage).	Uses sophisticated predictive formulae to combine condition-based diagnostics (such as temperature and vibrations) with the potential need for repair.
Utilizes static rules to make decisions.	Uses dynamic rules to make decisions.
Extremely susceptible to noise input.	Less susceptible to input noise.
A more effective approach to preventive maintenance that uses ongoing detection, diagnostic, and prognostic algorithms.	Preventive maintenance that uses algorithmic pattern recognition of machines is the most cutting-edge type.
Provides technicians with immediate notice when a problem arises.	Uses cutting-edge technology to forecast future breakdowns.

The advantages of CBM are (Zhou & Yin, 2019);

- Prolongs the life of the equipment because maintenance is done before it breaks.
- Due to the idea that maintenance is only done when necessary, hence is less expensive.
- Due to CBM being carried out while the asset is in use, normal operations are hardly ever interrupted.

- It is possible to schedule maintenance tasks to cut down on overtime expenses. Thus possible to do repairs off-peak.

The disadvantages of CBM are (Hiruta et al., 2019);

- It will cost a lot of money to train staff in the selected CBM technology. CBM systems barely detect fatigue failures.
- Installing condition-based monitoring systems is expensive.
- Harsh working conditions can damage sensors.
- It is difficult to predict when maintenance will be needed. It may require using an emergency budget.

When operating in a vast company CBM approach requires that different maintenance strategies are used. Preferably, CBM is used alongside a preventive maintenance strategy.

2.3 Obtaining data

The process includes finding out how long the machines in the critical section should go without repairs. Piqueras et al. (2019) stated that various machines yield different results depending on how the preventive maintenance is carried out. In this situation, the data on downtime has been sorted out and subjected to further analysis in order to reduce the time significantly.

2.3.1 Failure data

The failure data sorts the failure quantity in each department. Upon failure, the machine downtime is recorded for the purpose of maintenance optimization by minimization.

Failure leads to downtime, which in turn impacts the interest of the maintenance team, penalties, decent idle machines, loss of profit opportunity, non-growing benefit of the machine, and lost production (Piqueras et al., 2019). Based on the original equipment manufacturers (OEM), the root cause of the failure is determined for the critical machines. Failure can be categorized as mechanical or electrical using the severity and the probability of the failures in the entire department's control (Piqueras et al., 2019). Therefore, risk probability number is obtained. The failure data captured stemmed from a collection of cases that include improper use, inadequate materials, overstressed components, improper setup and improper installation. Other parameters are power surges, handling damages, and poor-quality control (Piqueras et al., 2019).

2.3.2 Failures and defects

Assessment of a textile mill should be done based on failures and defects occurrences and the impact of such occurrences on the maintenance strategy used. Indeed, the criticality of the equipment and the department under which the machines are located leads to the adaptation of a maintenance strategy. However, it is important to explore some of the failures and defects that are common in a textile mill [CITATION Hep16 \l 2057]. The failures are normally viewed as either known or unknown by the maintenance team. When the failures are known, such failures can be repetitive or non-repetitive. Li et al. (2019) claims that the repetitive failures are often associated with routine, preventive and statutory maintenance. On the other hand, non-repetitive failure attracts major repairs and overhauls. Sometimes, the failure could be unknown, leading to corrective action based on preventive maintenance. Also, a change of layout and restoration could demand the use of a breakdown maintenance strategy. In addition, the failures define the availability of the machines and the maintainability of such machines. A production line within the textile mills cannot be 100% perfect in their operation [CITATION Hep16 \l 2057]. At times, there are machine failures that can lead to stoppages of the equipment. Therefore, the duration that the machine is in operation can be treated as system availability. Maintainability implies the ease with which a machine can be maintained. In essence, it starts with the ability to identify the failure, the failure mode and the extent of the failure, and the ability to repair the failure in order to restore machine availability for production. Old machines were designed with each component functioning and failing independently of others. However, modern systems have modules that can easily be replaced as the other unit heads for repair. All the changes are aimed at improving the reliability of the textile machines. Li et al. (2019) claims that maintenance indirectly impacts the availability of machines through maintainability.

2.3.3 Common Waste in Maintenance Planning

A maintenance strategy tends to affect the time needed during the maintenance of the machines. Therefore, of the 8 hours of working, 4 hours of the maintenance team has been established to go to waste. Maintenance planning plays a crucial role in the development of the optimized maintenance strategy. Li et al. (2019) claims that a team of craftsmen can waste more time making multiple trips to the store in a bid to collect the materials. Such trips can accompany other trips such as going to find the tools needed for the operation. Much at times, the craftsmen can make irrelevant trips to the site where the machine to maintenance is located[CITATION She15 \l 2057]. Such trips include checking the nature of failure, checking the material requirement, checking the time required for the activity, and also assessing the extent of the damage. Such visits can be compressed when an optimized maintenance strategy is developed. Also, poor crafts coordination is quite a major issue during the maintenance of the machines. Therefore, it is important to have a plan that captures the desired number of craftsmen per machine. From Mostafa et al. (2015), incomplete planning and lack of effective communication can affect the nature of rolling out of the activities. Moreover, some of the craftsmen rely on the supervisor for guidance on how to operate the machine or perform maintenance. Such lack of expertise is a major cause of the poor maintenance plan in most organizations. Similarly, the habit of waiting for the next work always leads to the adoption of a poor maintenance plan. Most of the factories rely on Run to failure technique in order to administer maintenance activities. Such a technique leads to breakdowns that can affect machines' availability for quite a long time. Therefore, from[CITATION She15 \l 2057], a maintenance strategy that forces the craftsmen to waste time waiting for work is weak and not productive.

2.3.4 Failure Mode and Effect Analysis

The method is commonly used in identifications of possible failures based on a design looking into a manufacturing process, product, or service. The method entails the system analysis that is assessment based on planning and preparation part, structure analysis, and function analysis. In addition, the failure data and its analysis are assumed before the optimization is done to find out the criticality (Shahin et al., 2020). The value of severity from severity, occurrence, and detectability are multiplied in order to get the risk priority number. According to Shahin et al. (2020), the item with the highest risk priority number is given much attention. In a scenario where improvements of goals, development of new controls, and analysis of failures on an existing process, services, and product needs to be done, Failure Mode & Effects Analysis (FMEA) stands out (Sarih et al., 2018). Indeed, FMEA emerges as the solution when done periodically throughout the life of the processes.

2.4 Fishbone Diagram

The fishbone diagram is a cause-and-effect diagram that is useful in tracking down the reasons for certain events, imperfections, defects, variations, and failures. In maintenance, the tool can be useful in determining the maintenance strategies used in a given production process by assessing the various causes of the underlying event. In the manufacturing world, the fishbone diagram is defined by the 6 Ms that include machines, man, methods, materials, Mother Nature, and measurements (Ershadi et al., 2018). According to Ershadi et al. (2018), the 6 Ms tend to influence the variation in all the processes and act as the integral basis of the bones in the diagram.

2.5 Reliability and Response and Model significance

The ideas of reliability, response, and model significance can be applied to problems like inconsistent maintenance time scheduling and incoherent maintenance tactics. Inconsistency in maintenance time scheduling might lead to inconsistency in maintenance actions. Fan & Li (2020) researched that equipment may not be effectively maintained if maintenance is not performed consistently and according to a defined schedule, resulting in breakdowns, lower efficiency, and possibly hazardous conditions. As a result, it is critical to design a dependable maintenance schedule that is followed consistently. Maintenance employees may respond incorrectly or incompletely if maintenance strategies are incoherent. Fan & Li (2020) researched that maintenance employees may not offer accurate information regarding the condition of the equipment or the success of the maintenance strategies whenever they are not properly qualified or equipped to carry out maintenance tasks. Such a situation can result in insufficient or ineffective maintenance, increasing the risk of equipment failure and safety hazards. Maintenance time schedule inconsistency and incoherent maintenance techniques can also have an impact on the significance of maintenance models. Models based on erroneous or inadequate data may fail to accurately anticipate equipment performance or suggest effective maintenance procedures. This assumption of lack of close attention to data can result in lost time and resources, as well as increased safety and production concerns. To provide correct answers and dependable data for maintenance models, it is critical to develop reliable maintenance schedules and coherent maintenance strategies. This failure to act as per data and information can aid in maximizing equipment performance, lowering hazards, and optimizing resources.

A consistent maintenance schedule is essential for ensuring that equipment is properly maintained and runs efficiently. Duer et al. (2023) explains that uneven wear and tear on equipment can come from inconsistent maintenance plans, resulting in unscheduled downtime, increased repair costs, and safety issues. A dependable maintenance schedule, on the other hand, can help to discover possible concerns before they become serious ones, allowing maintenance professionals to take corrective action before a breakdown occurs. Incoherent maintenance techniques might cause maintenance employees to provide inaccurate or partial responses, limiting their capacity to effectively identify equipment issues and execute effective maintenance. Maintenance employees, for example, may be unable to identify the root cause of a problem or select the most effective maintenance approach if they are not properly trained to use diagnostic instruments or analyze maintenance data (Fan & Li et al., 2020). This failure to find root causes can lead to a waste of time and resources, as well as increased safety and production concerns. Maintenance models are useful for predicting equipment performance and determining the best maintenance techniques. However, in order to be useful, these models require accurate and reliable data. ÖzcAn et al. (2020) argues that inconsistent maintenance schedules and incoherent maintenance procedures might result in inadequate or erroneous data, affecting the model's validity. As a result, models may be less efficient in predicting equipment performance and identifying ideal maintenance techniques, resulting in wasted resources and increased safety and production hazards. To summarize, it is critical to establish consistent and dependable maintenance schedules as well as coherent maintenance strategies to ensure that maintenance professionals can respond to equipment concerns effectively and give correct data for maintenance models. This commitment to act on data and information can aid in optimizing equipment performance, lowering downtime and repair costs, and improving safety and production outcomes.

2.5.1 Mean Time between Failures

For repairable products, the reliability is quantified using Mean Time between Failures (MTBF). The formula for calculating the MTBF is given by (Duer et al., 2023);

$$MTBF = \frac{Total\,time}{Number\ of\ failures} \qquad 2.1$$

MTBF is a measure of how reliable a product is, and it is given based on the age (in unit hours) of the product. Furthermore, the higher the value of MTBF which is given in hours, the more reliable the product. The Mean Time Between Failures (MTBF) is a key statistic used in reliability engineering to assess the performance of a system or component. This indicator reflects the average amount of time between system or component failures (Duer et al., 2023). Understanding the MTBF is critical for planning effective maintenance and repair plans, as well as projecting systems or components expected lifetime. The range of reliability of the system components in the loom ranges from 1000 hours to 5000 hours as per the manufacture’s specification. The relationship between the number of failures and the average time between each failure is illustrated by a plot of MTBF and the failure number. Pena et al. (2022) stated that, the x-axis would reflect the number of failures, while the y-axis would represent the MTBF. The MTBF is calculated by dividing the total operating time by the number of failures. As the frequency of failures grows, the plot would indicate a falling trend in the MTBF over time. This trend is due to the fact that as a system or component fails more frequently, its dependability declines, resulting in a shorter MTBF (Pena et al., 2022). Variations in the MTBF may also be visible on the plot, indicating various failure modes or maintenance tactics. Pena et al. (2022) emphasized that a plot of MTBF and failure number is a useful tool for spotting patterns and trends in a system's or component's performance, and it can serve to inform maintenance and repair strategies to enhance dependability and minimize downtime. Consider the curves in Figure *2.3*;

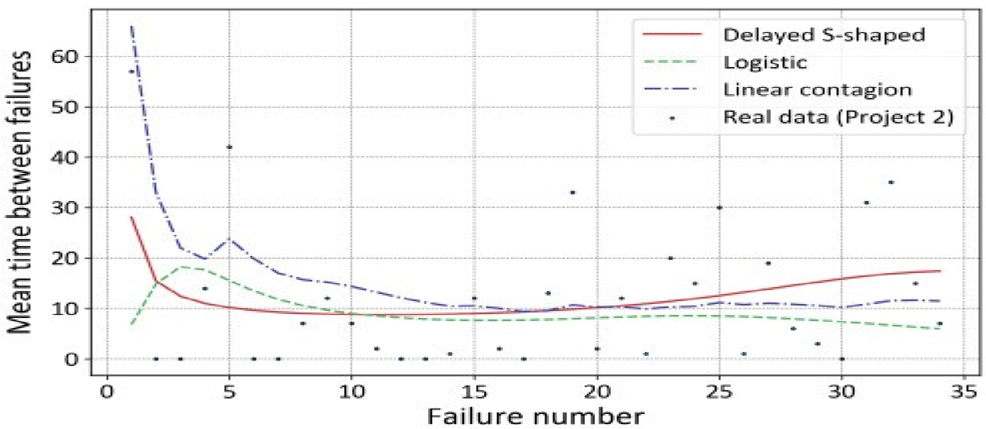


Figure 2.3: Plot of MTBF VS failure number (Pena et al., 2022)

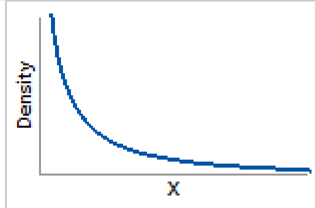
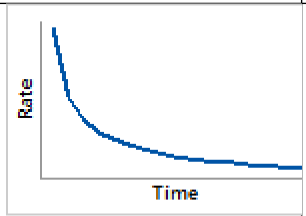
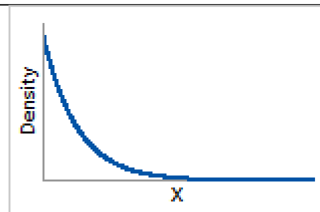
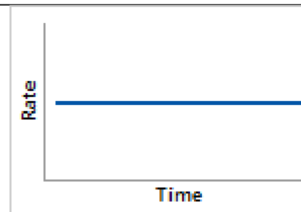
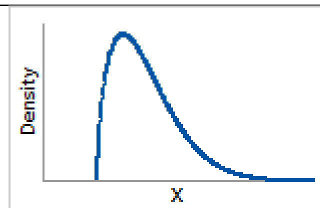
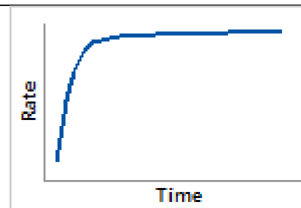
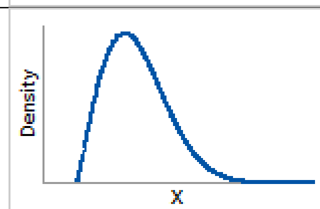
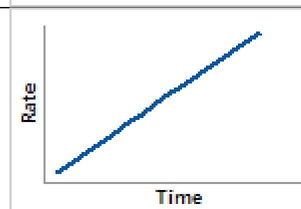
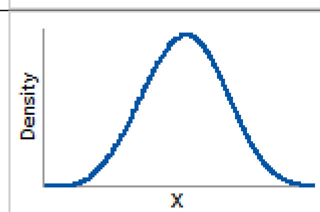
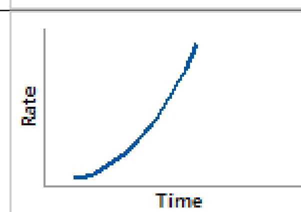
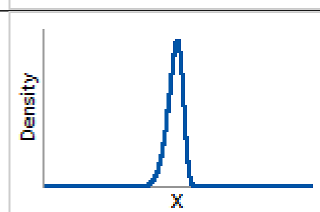
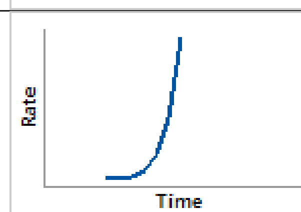
2.5.2 Regression

Regression is done to check whether the whole model being developed is statistically significant. A significant model has an R-square value greater than 0.70 or 70%. The value of MTBF is the response variable for the model. Regression analysis is one method for examining the link between the MTBF and other variables. ÖzcAn et al. (2020) argues that regression analysis is a statistical approach that allows us to determine the relationship between two or more variables and forecast how a change in one influence the others. The study discovers elements that lead to failures and devised ways to mitigate failures by using regression analysis on the MTBF.

2.6 The Weibull distribution

The Weibull distribution, a probability distribution widely used to describe mechanical system failure, is another key tool in reliability engineering. Weibull distribution was used to simulate the likelihood of failure over time and estimate the expected lifetime of a system or component (Fan & Li, 2020). Failure rate is determined, and predictions made about the future failures by fitting the Weibull distribution to failure data. The method was invented 70 years ago and has been extensively used for life or failure analysis (Zulkafli & Mat Dan, 2016). The data needed in Weibull distribution analysis is failure and change event data. Also, the operating age of the machine is required alongside the time when changes were made. Age can be elapsed calendar time is the machine run 24/7. Otherwise, age is given by operating hours or some kind of cyclic count. The Weibull shape that is < 0.9 implies a premature failures pattern. In this case, the applicable maintenance task is a root cause analysis. The method helps in eliminating the cause of premature failures. The approach is of low quality when it comes to maintaining equipment (Zulkafli & Mat Dan, 2016). The method is used on conditions in order to contain the effects of failure. A shape value that is 0.9 < shape (ß) < 1.3 describes a random failures pattern, and only on-conditions maintenance tasks are required as shown in Table 2.2 (Wisniewski, 2019). Furthermore, a ß > 1.3 follows a wear-out failures pattern that demands on-conditions and scheduled restoration or replacements of parts (Wisniewski, 2019). Wisniewski (2019) explains that a shape range of 1.3 to 2.5 implies weak wear out, and on-condition maintenance is preferred that includes scheduling restoration or replacement.

Table 2.2: The relationship between the parameters of the Weibull distribution, reliability functions, and hazard functions (Wisniewski, 2019)

Shape range	Probability density function	Hazard function	Failure
0 < ß < 1			Early failures occur throughout the product's first life cycle. To lessen the chance of first failure, these failures may demand a product "burn-in" period. From infinity, the value decreases exponentially. Failure rate is initially high but lowers over time (first section of "bathtub" shaped hazard function)
ß = 1			The rate of failure remains constant. Failures due to a variety of causes. Product "useful life" model. 1/ (= scaling parameter) decreases exponentially. Constant failure rate throughout product life (second portion of "bathtub" shaped hazard function)
ß = 1.5			Failure due to premature wear. Increases to a climax, and then lowers. Increasing failure rate, with the greatest rise occurring initially.
ß = 2			The risk of wear-out failure rises continuously during the product's lifetime. Rayleigh distribution is used. Failure rate increases linearly
3 ≤ ß ≤4			Failures due to rapid wear. Models the end-of-life era of a product, when the majority of failures occur. The form of a bell. it denotes rapid growth
ß > 10			Failures due to rapid wear. Models the end-of-life era of a product, when the majority of failures occur. The same as the extreme value distribution. Failures are rapidly rising.

2.6.1 Failure Rate vs. Time Plot

This refers to a plot of the failure rate over time. The plot has the cumulative failure rate or percentage on the y axis and the cumulative system operating hours on the x-axis. Li et al. (2019) explains that with this plot, one is able to depict the product failure rate at the time t. The Failure Rate vs. Time Plot is an important visualization tool in reliability engineering. This graphic visualizes a system's or component's failure rate over time, which can help us detect trends and patterns that may be indicative of certain failure processes (Heiser & Hofmeister, 2019). Li et al. (2019) concluded that one can build efficient maintenance and repair strategies to decrease the risk of failure and optimize the performance of the system or component by examining the Failure Rate vs. Time Plot. This aspect of Failure Rate vs. Time Plot has not been utilized in the case of REAL.

2.6.2 Fitting age data to a Weibull distribution

The estimation method for fitting age data to a Weibull distribution includes Ranked Regression, using the median ranks on the y values, Maximum Likelihood Estimation (MLE), and the Method of Moments. Method of the moment only takes into account the failure events hence not used for failures. The ranked regression method is preferred since the probability chart allows visualization of the data and the fit. In essence, it is easy to visualize whether the data suffers from a mixed failure mode or whether it is appropriate to use the location parameter from the visual line fit. The Weibull distribution is a powerful tool in modeling reliability data and predicting the failure behavior of systems. It is widely used in various industries, including manufacturing and engineering, to evaluate the probability of failures and optimize maintenance schedules. The Weibull distribution allows for the estimation of several key parameters, such as the shape and scale of the distribution, which can be used to calculate the probability density function, survival function, and hazard function. The hazard function describes the increasing failure rate of a system, with the largest increase occurring initially. Meanwhile, the probability density function increases to a peak and then decreases. The survival function is the probability that an item will survive until a particular time. In addition, the Weibull distribution provides insight into the expected percentage of items that will fail during the burn-in period, as shown in terms of the age of the machine. The probability plot can also indicate the time and scale of fast wear-out that is expected to occur, which is critical information for maintenance planning and optimization. Therefore, the use of the Weibull distribution and its associated functions can provide valuable insights into system reliability and help to minimize downtime and maintenance costs. The MLE method is often preferred when one has statistical background since it is more accurate. Li et al. (2019) found out that the MLE method has an inherent bias that can be worse when the shape parameter is < 1, and the number of data points is < 15 (Wisniewski, 2019).

2.6.3 The Optimized Maintenance Strategy

An optimized maintenance strategy implies that machines within the production floor are operated at optimized time schedules. An optimized maintenance strategy is normally aimed at helping the organization to meet the operational goals and has the overall lowest cost of operation. OEM does provide a maintenance strategy that often loses relevance with time as the machine wears down. In essence, Vasili et al. (2011) emphasizes that an optimized maintenance strategy helps in elongating the productive life of such machines. In essence, this is not the case in REAL.

2.6.4 Implementation of Maintenance Optimization

Maintenance optimization is a critical issue when it comes to the management of the production line [CITATION Meh11 \l 1033]. When a machine fails in the production line, it normally delays the completion time and leads to the rescheduling of other production activities that utilize the same line. Whenever jobs are not finished on time, the organization loses its credibility and trust from the customers. Therefore, optimization of the maintenance process involved the introduction of conditions and features into the maintenance schedule. Such a condition can only be unidentified by assessing the number of failures or failure rates over a period of time (the age of the machine). The shape parameters of the Weibull function provide the nature of failures, and therefore an appropriate approach to maintenance is determined. Vasili et al. (2011) states that the process of optimization ensures that the maintenance policy is more realistic and achievable. The end result of the optimization is that most of the imperfections, safety issues, and delays are eradicated from the maintenance system[CITATION Meh11 \l 1033].

2.6.5 The Validation of the Maintenance Strategy

The validation of a maintenance strategy is determining whether the strategy is effective in lowering the likelihood of equipment failure and enhancing system reliability. One method is to use regression analysis to analyze MTBF data (Marcello, 2020). Fitting a mathematical model to the MTBF data to detect any correlations between the maintenance plan and the MTBF is what regression analysis is all about. This approach can assist in establishing whether the maintenance method is effective in reducing failure frequency and improving system reliability. In such cases, Da Silva et al. (2020) suggested that one should collect MTBF data for the device over a specified time period.

The period between failures, the cause of the failure, and any relevant maintenance information should all be included in this data to determine the variables that may be influencing the MTBF, such as maintenance plan, equipment age, and operating conditions. The type of data and the nature of the relationship between the independent and dependent variables are used to select the right regression model, using a statistical software application to fit the model to the MTBF data. According to Marcello (2020), maintenance teams are able to determine the strength of the association between the maintenance strategy and the MTBF as a result of this time schedule. ÖzcAn et al. (2020) concluded that the model is then evaluated to confirm that it is a good fit for the data and offers accurate MTBF estimates to draw judgments about the effectiveness of the maintenance plan and whether any enhancements or revisions are needed based on the results of the regression analysis. Doing regression analysis on MTBF data can aid in validating the efficacy of a maintenance approach and identifying areas for improvement to ensure optimal equipment performance and reliability.

2.7 Current Maintenance Strategies at REAL

In the weaving department, the efficiency of the machine is < 90%, making it a critical section in the weaving department. There are 88 machines that are critical in fabric formation, and an overview of a section of the machines yields crucial assertions on the maintenance. From Figure 2.4, both rapier and air-jet loom comprised of 66 machines which form the critical equipment as far as maintenance and availability for production is concerned.

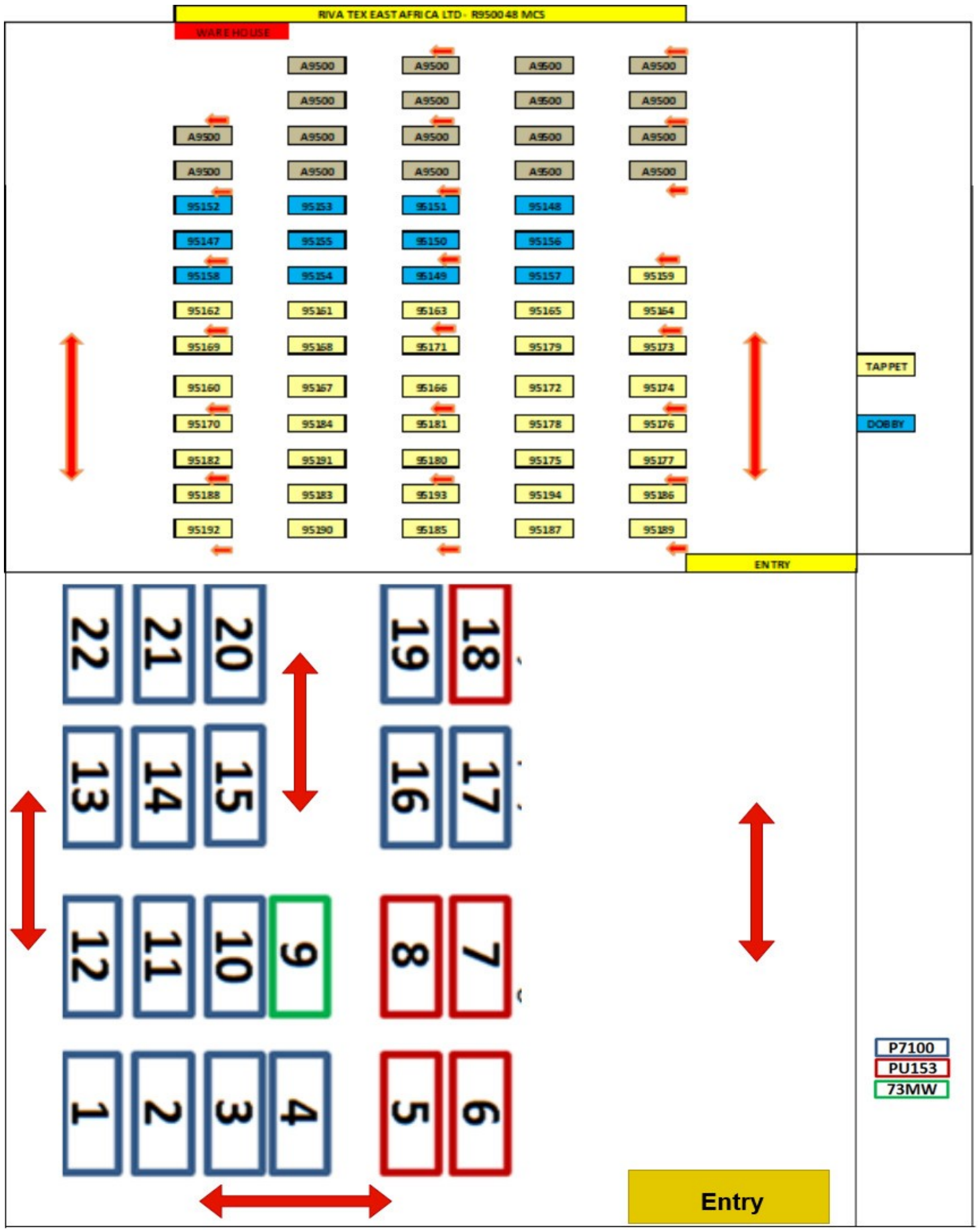


Figure 2.4: The layout of a section of weaving machines (REAL maintenance department)

Type of failures experienced in the spinning department includes Mechanical: Bearing, loose nuts, broken parts, and Electrical: Motor (brushes, fuses, switches).

A sampled performance of the machines based on their availability in a shift is shown in Figure 2.5.

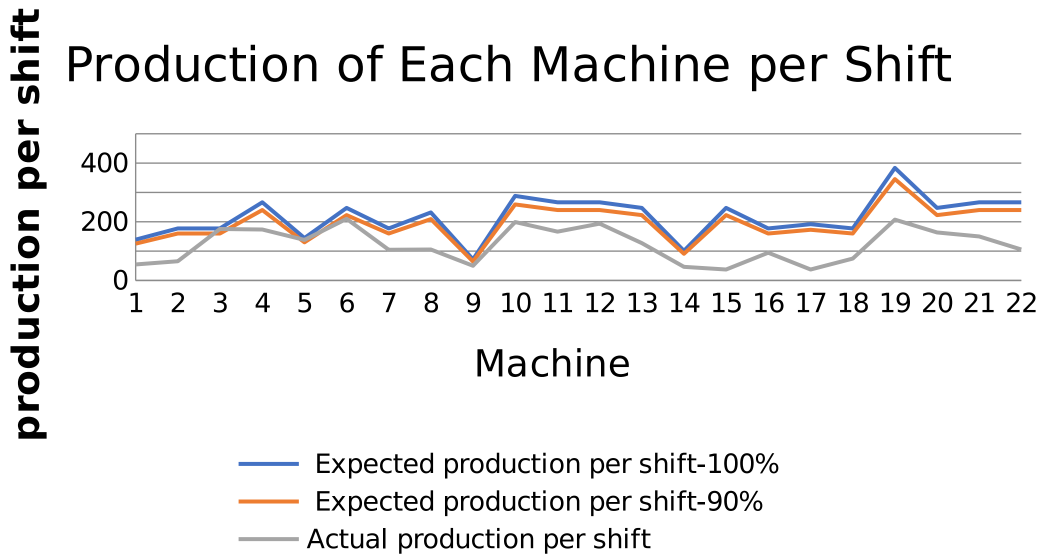


Figure 2.5: Performance of the machines (REAL maintenance department)

The rapier and the air-jet loom handle the majority of the designs on the factory floor, while the projectile technology weaves designs with large size. Figures 2.6, 2.7, 2.8, and 2.9 shows the state of maintenance of the rapier and air-jet looms. Similarly, from these pictures, it is easy to identify the push factors that lead to failures within the weaving section. The factors can be avoided by the implementation of a proper maintenance schedule and approach.

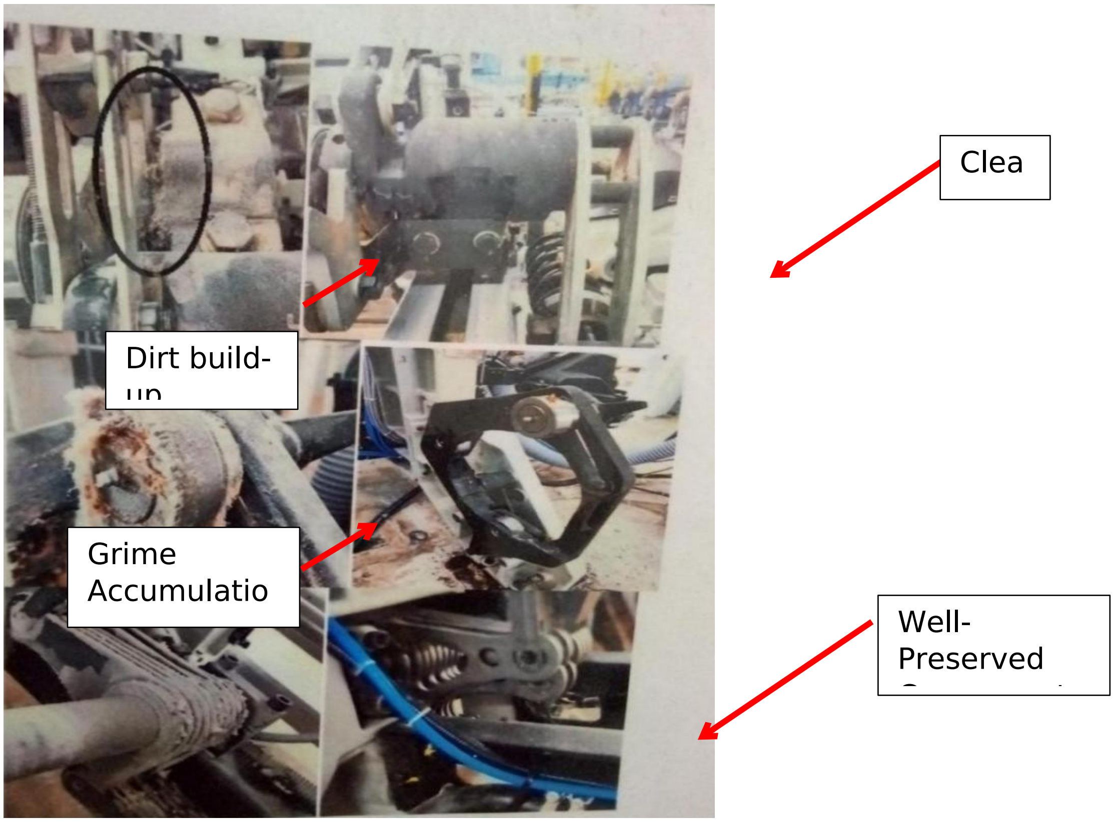


Figure 2.6: Buildup of dust and fiber waste of moving machine parts (REAL maintenance department)

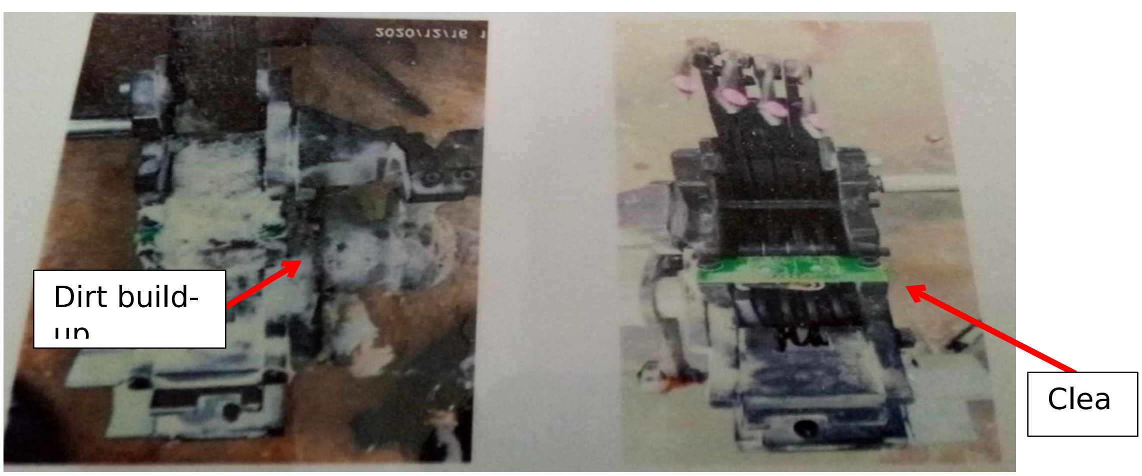


Figure 2.7: Weft selector covered by choking fiber waste (REAL maintenance department)

Figure.2.8: Sample of belt that depicts early worn-out failure (REAL maintenance department)

Figure 2.9: A scenario of a cleaned machine part with a brush leaving no choked gears with waste (REAL maintenance department)

Furthermore, Figures 2.6, 2.7, 2.8, and 2.9 indicate a lack of optimized and consistent maintenance practices that are required in ensuring that the equipment life is increased, and that premature failure is avoided. The increased wear-out failures are more likely when the machines are operated under the "not good" situation in Figures 2.7 and 2.8. Also, the “not good” situation in Figures 2.7 and 2.8 indicates a lack of an optimized maintenance strategy. From Figures 2.6, 2.7, 2.8, and 2.9, the critical equipment has built-up wastes that choke the gears and the moving parts. REAL is divided into 3 departments with various cost centers. The department in question is the weaving department. The machines are part of the production line; therefore, any stoppage implies a halt in the entire production. In essence, it is a cloth-forming section. The state of the machines determines the quality of the cloth produced. Removing the weaving machines from the production line implies that key activities at REAL are stopped. Therefore, maintenance of machines in the department must remain as a shop floor activity. The current maintenance practices are based on breakdown and preventive maintenance strategies which is dominated by some incoherence and inconsistency as far as time scheduling is concerned.

2.8 Research Gaps

One significant source of concern is the aspect of mechanical, human, and systemic failures. Much has been written about mechanical failures, but little about human and societal failures. Weaving machines are prone to mechanical, human, and systemic failures, making maintenance essential to their proper operation. Weaving machines have several moving parts that are susceptible to wear and tear as well as various forms of mechanical failure. Belts, for example, may slip or break, bearings may wear out, and gears may get misaligned. Mechanical failures can result in decreased production, poor output quality, and, in certain situations, full machine breakdowns. Weaving machine operators might also contribute to their failure. An operator, for example, may overload the equipment, employ inappropriate settings or operating techniques, or just disregard essential maintenance responsibilities. These errors can damage the equipment, diminish its efficiency, and jeopardize the output quality. Finally, systemic failures might arise as a result of variables outside of the control of individual operators or maintenance specialists. A power loss or voltage surge, for example, could harm the machine's electrical components. Changes in ambient circumstances, such as temperature or humidity, can also have an impact on the machine's operation. Given these possible failure points, it is evident that frequent maintenance is essential for the correct operation of weaving machines. Proper maintenance can help to reduce breakdowns, boost production, and improve output quality. It can also assist in identifying and addressing issues before they become more serious and costly ones.

The argument made by Mahfoud et al. (2016) is that proactive strategies such as predictive and preventive maintenance are essential for maximizing the availability of weaving machines. These strategies involve regularly monitoring the machines for signs of wear and tear, and conducting maintenance and repair work before a breakdown occurs. However, the credibility of the manufacturer's recommendations for maintenance practices needs to be assessed, as some may not be optimal for specific machine configurations or conditions. To optimize preventive maintenance, Mahfoud et al. (2016) propose that critical equipment needs to be identified and prioritized for maintenance. This involves evaluating the likelihood and impact of failures on the machine's overall performance, as well as the cost of maintenance versus the cost of downtime. However, they do not provide a basis for finding critical equipment, and this could be an area for further research. Another proposed direction for preventive maintenance optimization is the simulation of big data. By analyzing large datasets generated by weaving machines, it may be possible to identify patterns and trends that can inform maintenance decisions. This aspect could involve using machine learning algorithms to identify potential failure modes or predicting the remaining useful life of critical components. Overall, Mahfoud et al. (2016) argue that proactive maintenance strategies are necessary for maximizing the availability of weaving machines. However, the credibility of manufacturer recommendations needs to be assessed, and further research is needed to identify critical equipment and optimize preventive maintenance using big data analysis. Piqueras and Fernandez-Crehuet (2019) argue that preventive maintenance is an important strategy for avoiding unexpected breakdowns of weaving machines. This approach involves analyzing data collected over a long period of time to identify patterns and trends that can inform maintenance decisions. By conducting regular maintenance and repair work based on this data, it is possible to minimize the risk of machine breakdowns and maximize their availability for use. However, one issue that Piqueras and Fernandez-Crehuet (2019) were not able to address is that identical equipment does not necessarily mean identical maintenance strategies. Different weaving machines may be subject to different operating conditions, such as variations in temperature, humidity, or the type of material being woven. These differences may affect the wear and tear on different parts of the machine, and as a result, require different maintenance strategies. To address this issue, it is important to conduct a thorough analysis of each weaving machine and its operating conditions. This undertaking may involve collecting data on factors such as the machine's age, usage patterns, and environmental conditions. By considering these factors, it is possible to develop customized maintenance strategies that are tailored to the specific needs of each machine. In addition, it may be useful to incorporate real-time monitoring systems into weaving machines, which can provide continuous data on their performance. This data can help identify potential problems as they arise, allowing for quicker and more targeted maintenance interventions. By combining both long-term data analysis and real-time monitoring, it is possible to develop a more comprehensive and effective preventive maintenance strategy for weaving machines.

Li et al. (2016) argue that maintenance can indirectly impact the availability of weaving machines through its impact on maintainability in multi-component systems with hierarchical dependence. In such systems, the failure of one component can lead to the failure of other components that depend on it, resulting in decreased machine availability. While Li et al. (2016) addresses the issue of multi-component systems with hierarchical dependence; they fail to use data to address the issue of failure in system components with the aim of optimization. To optimize maintenance in such systems, it is important to identify which components are critical to the functioning of the machine and prioritize their maintenance accordingly. This requires collecting and analyzing data on the performance of each component, as well as the interdependencies between them. One approach to using data to optimize maintenance in multi-component systems is to use predictive maintenance techniques. These techniques involve analyzing data on the performance of each component, such as temperature readings or vibration levels, to identify potential failures before they occur. By identifying potential issues early, maintenance can be scheduled and conducted proactively, reducing the risk of unexpected downtime. Another approach is to use machine learning algorithms to analyze data on the performance of each component and identify patterns and trends that can inform maintenance decisions. For example, machine learning algorithms can be used to identify which components are most likely to fail, or which maintenance strategies are most effective for different types of components. By using data to inform maintenance decisions, it is possible to optimize maintenance in multi-component systems with hierarchical dependence, maximizing machine availability and minimizing downtime. Overall, while Li et al. (2016) addresses the issue of multi-component systems with hierarchical dependence, using data to optimize maintenance can further enhance the effectiveness of maintenance strategies. By analyzing data on the performance of each component, it is possible to identify potential issues early and prioritize maintenance, accordingly, maximizing machine availability and minimizing downtime.

Mostafa et al. (2015) argue that maintenance strategies can have an impact on the time required for maintenance activities in weaving machines. According to lean thinking, maintenance can be optimized by reducing waste and streamlining maintenance value stream mapping. In this context, Mostafa et al. (2015) proposed a scheme of lean maintenance practices that could be applied to weaving machines. However, while Mostafa et al. (2015) mentioned waste reduction, maintenance value stream mapping, and lean maintenance practices, they failed to mention the specific tools used in lean maintenance. These tools are important for identifying and eliminating waste in maintenance activities and improving the efficiency of maintenance processes. One example of a tool used in lean maintenance is the FMEA methodology. This methodology involves organizing the workplace to optimize efficiency, with a focus on sorting, simplifying, sweeping, standardizing, and sustaining. By applying this methodology to maintenance activities, it is possible to eliminate waste and improve the efficiency of maintenance processes. Overall, while Mostafa et al. (2015) proposed a scheme of lean maintenance practices for weaving machines, they failed to mention the specific tools used in lean maintenance.

Sarih et al. (2018) suggested that the failure mode and effects analysis (FMEA) approach can be used to improve the goals, develop new controls, and analyze failures in an existing process. They proposed a methodology for identifying important components of a specific industrial system based on experience input. While Sarih et al. (2018) conducted a literature review on the use of FMEA in industrial systems, although they did not rank equipment based on criticality due to failures. However, ranking equipment based on criticality is important to prioritize maintenance activities and optimize the maintenance process. One approach to ranking equipment based on criticality is to use a risk matrix. This action involves identifying the likelihood and severity of failure for each equipment component and plotting these on a matrix. The resulting plot can then be used to prioritize maintenance activities based on the level of risk associated with each component.

Ershadi et al. (2018) proposed the use of the fish-bone diagram in the manufacturing world, which is defined by the 6 Ms that include machines, man, methods, materials, Mother Nature, and measurements. This tool is used to identify the various causes and effects of a problem, which can be used to develop effective solutions. However, Ershadi et al. (2018) work missed out on the opportunity to identify all the causes of inconsistency in scheduling machine maintenance. In order to identify all the causes of inconsistency in scheduling machine maintenance, it is important to consider various factors that could impact maintenance scheduling. These factors may include the availability of maintenance personnel, the availability of spare parts, the complexity of the maintenance task, the frequency of machine use, and the production schedule. One approach to identifying these causes is to conduct a root cause analysis (RCA), which involves identifying the underlying causes of a problem. RCA can help to identify the factors that contribute to inconsistency in scheduling machine maintenance and can provide insight into how to address these issues. Another approach is to use data analytic to identify patterns and trends in machine maintenance. By analyzing historical maintenance data, it may be possible to identify factors that contribute to inconsistency in scheduling machine maintenance. This information can be used to develop predictive maintenance models, which can help to optimize maintenance scheduling and reduce downtime. In conclusion, while Ershadi et al. (2018) proposed the use of the fish-bone diagram to identify the causes of problems in the manufacturing world, their work missed out on the opportunity to identify all the causes of inconsistency in scheduling machine maintenance. To address this concern, it is important to consider various factors that could impact maintenance scheduling, and to use tools such as RCA and data analytic to identify underlying causes and develop effective solutions.

Wisniewski (2019) stated that the Weibull distribution requires the operating age of the machine, as well as time changes, to accurately predict equipment failure rates. While, this is a useful tool for understanding equipment failures, Wisniewski's (2019) work did not use the Weibull function alongside Monte Carlo simulation to assess the nature of equipment failure in a textile mill setup or factory. Monte Carlo simulation is a statistical technique that can be used to model complex systems and simulate outcomes under various conditions. By combining the Weibull distribution with Monte Carlo simulation, it is likely to create a more comprehensive model of equipment failure rates that takes into account various factors that may impact the performance of the machine. Additionally, Wisniewski (2019) stated that Monte Carlo simulation can also be used to evaluate the effectiveness of different maintenance strategies. By simulating different maintenance scenarios and comparing the results, it is possible to identify the most effective maintenance approach for a given machine or system. While, Wisniewski (2019) work highlighted the importance of the Weibull distribution for understanding equipment failures, their work did not use this function alongside Monte Carlo simulation to assess the nature of equipment failure in a textile mill setup or factory. By combining these tools, it is important to create more comprehensive models of equipment failure rates and identify potential issues before they occur.

Zulkafli & Mat Dan (2016) used Weibull analysis to investigate the maintenance performance of a gasification process unit, which is a useful tool for understanding equipment failure rates. However, their work did not address the use of Weibull analysis to investigate the maintenance time schedules in critical equipment. One potential application of Weibull analysis in maintenance scheduling is to determine the optimal time for maintenance activities. By analyzing equipment failure data using the Weibull distribution, it is important to identify the most common failure modes and determine the expected time to failure. This information can then be used to schedule maintenance activities before equipment failure occurs, thereby reducing downtime and improving productivity. In addition, Weibull analysis can also be used to identify trends in equipment failures over time. By analyzing failure data over an extended period, it is possible to identify changes in failure rates that may indicate a need for changes in maintenance strategies or equipment replacement. Therefore, while Zulkafli & Mat Dan's (2016) work demonstrated the usefulness of Weibull analysis in investigating maintenance performance of a gasification process unit, further research is needed to explore the potential of this tool in optimizing maintenance schedules for critical equipment in various industries.

Vasili et al. (2011) suggested that the optimization of maintenance systems can help to eliminate imperfections, safety issues, and delays. However, their work failed to capture the issue of inconsistency scheduling of machine maintenance, which can have a significant impact on the effectiveness of maintenance programs. Inconsistent scheduling of machine maintenance can lead to increased downtime, reduced productivity, and higher costs. When maintenance activities are not scheduled and performed on a regular basis, equipment failures and breakdowns are more likely to occur. This scenario can lead to unplanned downtime, production delays, and increased maintenance costs. To address the issue of inconsistent scheduling of machine maintenance, it is important to establish a regular maintenance schedule and adhere to it. This argument can help to prevent equipment failures and reduce the risk of downtime. In addition, using data analytic and predictive maintenance tools can help to identify potential equipment issues before they become major problems, allowing for proactive maintenance and reducing the need for reactive maintenance activities. Therefore, while Vasili et al. (2011) highlighted the benefits of optimizing maintenance systems, it is important to address the issue of inconsistent scheduling of machine maintenance to fully realize these benefits. By establishing a regular maintenance schedule and utilizing predictive maintenance tools, organizations can improve the effectiveness of their maintenance programs and reduce the risk of downtime and production delays.

In this research study, significant value was added by addressing the gap in inconsistent scheduling of machine maintenance and incoherent maintenance strategies. The utilization of Failure Mode and Effects Analysis (FMEA) and fishbone diagrams proved to be highly effective in identifying critical equipment and identifying the root causes of failures in textile mills. By employing FMEA, the researcher was able to systematically analyze potential failure modes and their associated effects on the machinery within the mills. This approach not only helped in identifying the most critical equipment prone to failures but also prioritized maintenance efforts based on the severity of the potential consequences. Consequently, this study enabled the mills to focus their resources and attention on those machines that had the highest likelihood of causing significant disruptions if not properly maintained. Additionally, the utilization of fishbone diagrams in this research study provided a visual representation of the various factors contributing to maintenance issues. By categorizing the potential causes into specific branches on the diagram, it became easier to identify the root causes of failures and maintenance inconsistencies. This analysis helped the textile mills gain a comprehensive understanding of the underlying issues and develop targeted strategies to mitigate the failures. In a nutshell, by employing FMEA and fishbone diagrams, this research study not only highlighted the critical equipment requiring maintenance attention but also provided valuable insights into the root causes of maintenance inefficiencies. The findings of this study can serve as a basis for implementing more effective maintenance scheduling and strategies in textile mills, leading to improved operational efficiency, reduced downtime, and increased productivity.

CHAPTER THREE: METHODOLOGY

This chapter outlines the procedures employed to accomplish the research objectives. Prioritizing the department that requires maintenance arises from the criticality ranking assessment. Machines within Rivatex East Africa Limited receive unstructured and unscheduled OEM-based maintenance. The judgment can be done by way of maintenance strategy assessment. In addition, the parameter that is used in the analysis in the case of FMEA entails the quantity of failures in each department. The Weibull distribution analysis, on the other, hand uses the failure data and age of the machine in the analysis.

The research began with preliminary surveys that involved conducting interviews and administering questionnaires to gather initial data. By obtaining an accurate picture of the real situation, the study focused on reviewing the existing literature to assess the underlying problem as evaluated by other scholars. This process helped to identify gaps and formulate the research problem. Data collection was carried out in real-time, capturing information on failures, machine age at the time of failure, and maintenance strategies. The collected data underwent processing for Monte Carlo simulation. FMEA was employed to determine the critical equipment, while a fishbone diagram was used to identify failure causes. Weibull distribution analysis was conducted to calculate the data distribution, deriving shape and scale parameters for generating random data representing 1000 instances of similar machine scenarios. MTBF was calculated for these randomly generated data instances. Subsequently, the data underwent Monte Carlo simulation to evaluate performance maintenance in various time schedules as shown in Figure 3.1.

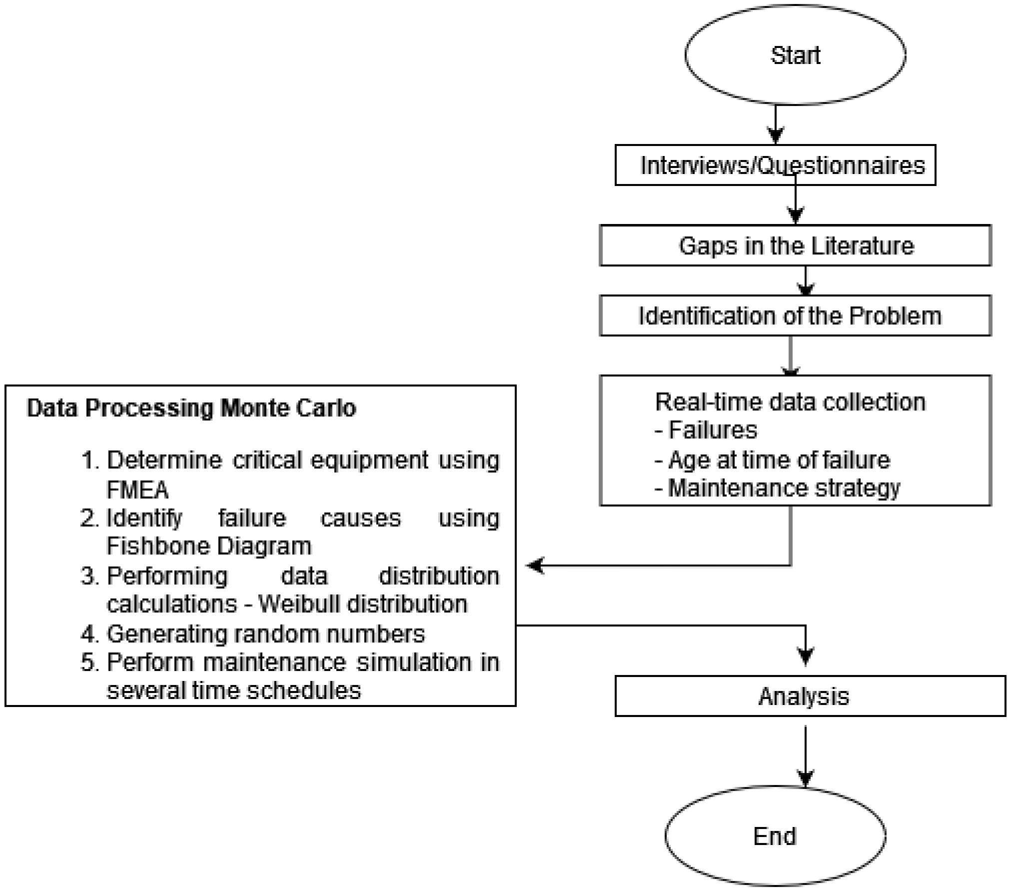


Figure 3.1 Conceptual Framework

Real-time data collection is a critical process that can provide valuable insights into the performance of systems and equipment. One area where real-time data collection is particularly useful is in monitoring failures, including tracking the age of equipment at the time of failure. By collecting and analyzing this data, organizations can develop effective maintenance strategies that help to prevent future failures and minimize downtime. Real-time data collection is essential for monitoring failures, including tracking equipment age at the time of failure, and developing effective maintenance strategies. With one year of data collection, organizations can gain a better understanding of failure patterns and make informed decisions about maintenance schedules. The methodology was carefully selected based on its ability to provide accurate results, the availability of resources required for its implementation, and its compatibility with the data available. This approach was deemed to be the most appropriate due to its proven track record in producing reliable results, its ease of use, and its alignment with the specific requirements of the project. By using this methodology, the author was able to collect high-quality data that can be confidently used to inform decision-making.

3.1 Method of Data Collection

During situation analysis, data collection was done using observation, check sheets, interviews, and questionnaires with both open and closed-ended questions. Each personnel or participant was presented with a questionnaire. The check sheet was filled while at the same time monitoring the failures in the entire weaving section. A repeat of the same was done for a month in the critical machines. Interviews were conducted with 20 members of REAL's maintenance staff. This procedure entailed asking them a series of questions in order to learn about their work experiences, responsibilities, and the obstacles they confront while doing their duties. REAL can acquire significant insights into the experiences of their maintenance employees by conducting these interviews. The information gleaned from the interviews can be utilized to identify areas for improvement in the operations of the maintenance team and to build plans to increase their overall performance. Furthermore, the interview input can be utilized to identify training gaps and improve communication between the maintenance team and other departments within the firm.

3.1.1 Interviews with Maintenance Team

The maintenance teams were interviewed to provide important information as far as the maintenance strategies are concerned. In essence, interviews formed the basis of mapping the maintenance strategy of the critical equipment. Interviews provided information on the maintenance strategies and the critical equipment at REAL. The interviews provided both qualitative and quantitative information that can be interpreted. Given that interviews were structured, unstructured, and semi-structured, the most important aspect of the method was the data collected (Fredriksson & Larsson, 2012). Finally, all the interview questions are provided in appendix 1. The interview process was thorough, consisting of 4 thoughtfully crafted questions that aimed to capture key insights from the maintenance team. It is evident that the team approached the interview process with a high level of engagement, as all the questions were attempted and answered to the best of their ability. This level of commitment to providing detailed and insightful responses undoubtedly proved invaluable in the analysis of the data collected.

3.1.2 Questionnaires to Maintenance Staff

A list of questions was prepared in order to help in data collection concerning REAL's maintenance strategies. A series of open-ended questions provide the respondents with an opportunity to express their critical thinking concerning the state of machine maintenance at REAL[CITATION Mil16 \l 1033]. Also, closed-ended questions are quite important in restricting the depth of response. Most of the machine operators and the maintenance provided information on failure rates, downtime, and the duration needed to scan for failures. The questions used in this process are provided in appendix 2. The maintenance team was diligent in their response to the survey, as all 23 questions were thoughtfully filled out and returned. This level of attention to detail ensures that the collected data is comprehensive and accurate, providing valuable insights for analysis and decision-making.

3.1.3 Real-time data collection on Maintenance Activities

Recording the maintenance sessions and activities at REAL was captured through an observation process. In this method, data pertaining identification of critical failure type, number of failures, availability, downtime, and the productivity of the machines were collected. The work performance during most of the maintenance and installation process was captured and used for the analysis and development of the optimized maintenance strategies. Observation notes and images are provided in appendix 2.

3.2 Method of Data Analysis

The data collected in the field was recorded statistically for the purpose of use in failure mode and effect analysis, fishbone diagram analysis, and Weibull distribution analysis. Following the completion of Weibull analysis, the collected data underwent both Monte Carlo simulation and regression analysis to extract further insights and ensure data validation.

3.2.1. Data Processing using Monte Carlo

Data Processing using Monte Carlo is an effective method for evaluating and predicting equipment failure modes, with several steps involved. The first step is to determine the critical equipment using Failure Mode and Effects Analysis (FMEA) to identify equipment failure modes and their potential effects. A fishbone diagram can then be used to identify underlying failure causes. To further enhance the analysis, performing data distribution calculations using the Weibull distribution can provide insight into equipment reliability and predict potential failures. Once potential failures have been identified, random number generation can be used to simulate maintenance activities in several time schedules. Utilizing these tools and techniques can provide organizations with a comprehensive understanding of equipment criticality, help predict and mitigate potential failures, and develop effective maintenance strategies to optimize performance and reduce downtime.

The overall procedure is as follows (Shahin et al., 2020);

i. Determine critical equipment using FMEA.
ii. Identify failure causes using Fishbone Diagram.
iii. Performing data distribution calculations.
iv. Generating random numbers.
v. Perform maintenance simulation in several time schedules.

3.2.2 Determining the critical equipment

In this case, Failure mode and effect analysis (FMEA) presents a basis of risk assessment of the machines as far as failures and downtime are concerned. FMEA procedure is as follows (Shahin et al., 2020);

i. Identifying all the probable failure modes from data collected through interviews, interviews as well as real-time data collection.
ii. Assign a value on a 1-10 scale to severity, probability of occurrence, and the probability of detection for each potential failure mode.

iii. Get the Risk Priority Number (RPN) by multiplying the three numbers for each failure mode.

$$RPN = (Severity * Occurence * Detection) \qquad 3.1$$

iv. Using RPN as the priority value, rank the failure modes. The highest score demands the most urgent improvements activity. For instance, if there are three items of comparison and the RPN score are 11, 24 and 32. Then score, 32 has the highest RPN and should get the highest priority for corrective measures.

3.2.3 Fishbone Diagram process

In this study, the construction of the fishbone diagram involved initiating the process by drawing a horizontal line and placing the problem statement at one end, which in this case pertained to the inconsistent and incoherent maintenance strategy, particularly in relation to the machines (Ershadi et al., 2018). A slanted line was then drawn, pointing towards the statement, with a box positioned at the end to represent the fish's head. The analysis further identified the 6 Ms as factors contributing to the run-to-failure problem. Smaller lines branching off each bone with 6 Ms were drawn and labeled with a factor that impacts the category. The procedure was as follows (Ershadi et al., 2018);

i. Define the problem to be solved in relation to maintenance strategy.

ii. Establish the main causes of the inconsistent and incoherent maintenance strategy.

iii. Establish the reasons leading to the inconsistent and incoherent maintenance strategy.

iv. Establish the most likely causes of inconsistent and incoherent maintenance strategy.

3.2.4 Weibull distribution

A Weibull distribution presents 2 parameters that define it, shape and scale parameters. The critical machines are rapier weaving machines and air-jet weaving machines. The input data from the rapier weaving machine were collected from the Reed system (X_1), warp let-off system (X_2), fabric take-up system (X_3), machine main drive system (X_4), selvedge formation system (X_5) and connectivity system (X_6). On the other hand, maintenance input data from air-jet weaving machines were collected from the weft feeders system (X_7), reed system (X_8), warp let-off system (X_9), fabric take-up system (X_{10}), machine drive system (X_{11}), harness frames system (X_{12}), selvedge formation system (X_{13}) and connectivity system (X_{14}) as shown in appendix 3.

For the critical equipment, lubrication fabric take-up and let-off system (X_{15}), lubrication main drive (X_{16}), total time operation time (X_{17}), and the number of failures (X_{18}) were subjected to simulation. Therefore, all these formed the input variables. The output variable was calculated from the total time of operation and the number of failures in the critical machines, MTBF (Y). It is important to mention that all data for a 2-parameter Weibull distribution must be greater than zero. Since the threshold parameter is zero. The shape parameter describes how the data are distributed. Whereas lower shape values describe the right-skewed distribution, and higher shape values describe the left-skewed distribution. The shape of 3 describes a normal curve.

Measurement of the distance between the fitted line based on the Weibull distribution and the empirical distribution resulting from the data points is done using the Anderson-Darling goodness-of-fit statistic (AD-Value) (Jäntschi & Bolboacă, 2018). AD is given as the squared distance that is weighted more heavily in the tails of the Weibull distribution. A smaller value provides stronger evidence that the data follows a Weibull distribution.

On the other hand, the scale parameter describes how spread out the data is in the distribution. A large-scale result depicts a more spread-out distribution. In order to model the maintenance strategy at the critical department, a Weibull Distribution was selected to analyze the collected data of machine failure with the age of machines. This project adopted a **3-parameter probability density similar to recommendation by** Wisniewski (2019)**.** In this case, the location parameter is equal to 0 in **3-parameter probability density function and the** Weibull Distribution was given by (Wisniewski 2019);

$$f(x)=\frac{\gamma}{\alpha}\left(\frac{x-\mu}{\alpha}\right)^{\gamma-1}\exp\left(\left(\frac{x-\mu}{\alpha}\right)^{\gamma}\right)\ x\geq\mu;\gamma,\alpha>0 \qquad 3.2$$

Where,

- γ is the **shape parameter or** Weibull slope or the threshold parameter **similar to recommendation by** Wisniewski (2019).
- α is the **scale parameter** or the characteristic life parameter in line with the suggestion put forth by Wisniewski (2019).
- μ is the **location parameter** or the waiting time parameter or sometimes the shift parameter akin to the suggestion put forth by Wisniewski (2019).

The next step was to simulate the systems using the formula;

$Weibull = ¿¿ + min$ 3.3

Where;

- *c* is scale
- *m* is shape
- *min* is the minimum value of the age of the system.

Referring to Table 2.2 in page 23 and 24, the Weibull distribution has the capability to represent data that have a right, left, or symmetric skewness. Weibull distribution can also model a hazard function that is decreasing, increasing, or constant, enabling the model to describe any stage of an object's lifespan. The impact of the shape parameter on the data is significant (Wisniewski, 2019). The shape parameter characterizes the distribution of the data. The shape value of 3 was similar to a normal curve. When the shape value was low, such as 1, the curve was skewed to the right. On the other hand, when the shape value was high, such as 10, the curve was skewed to the left. The scale parameter has a significant impact on the Weibull curve (Wisniewski, 2019).

The scale, also known as the characteristic life, is the point at which 63.2% of the data is < it scales value. The scale parameter in a distribution account for the level of variability present. The scale parameter determines the position of the Weibull curve in relation to the threshold, like how the mean determines the position of a normal curve. If the scale parameter is set to 20, for instance, it implies that 63.2% of the equipment will fail within the first 20 hours after the threshold time (Wisniewski, 2019). Adjusting the scale parameter has an impact on the extent to which the probability distribution spreads out. When the scale is increased, the distribution stretches out to the right, resulting in a decrease in its height as shown in Figure 3.2.

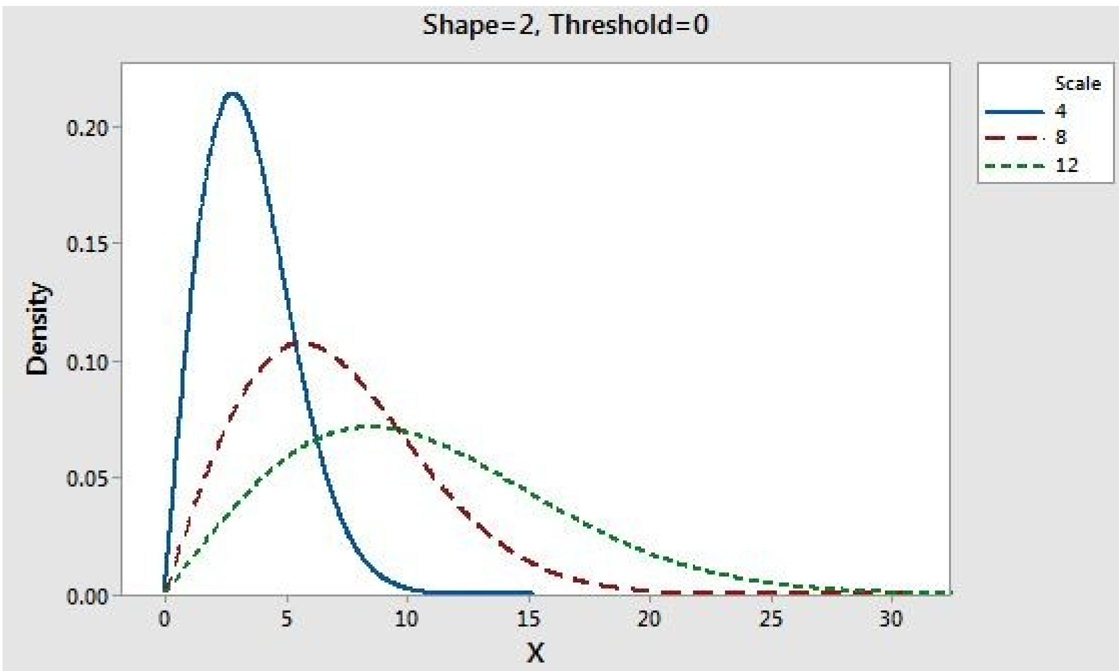


Figure 3.2: Weibull Scale Parameter

The procedure that was used to perform Weibull distribution;

i. Step 1: Determine the age of the machine and failure data resulting from the inconsistent and incoherent maintenance strategy used at REAL.
ii. Step 2: Record the number of failures over the machine age at REAL.
iii. Step 3: Find the cumulative age alongside the number of failures of the machines.
iv. Step 4: Fitting age data to a Weibull distribution.

v. Step 5: Calculate the MTBF as shown in equation 2.1.

vi. Step 6: Plot the Weibull distribution.

vii. Step 7: Undertake probability plot based on MLE.

viii. Step 8: Analyze the data by checking the shape value.

ix. Step 9: Perform regression analysis to validate the models used and determine the R-square value. The validation was done on a total of 18 models and finally on the MTBF by checking the sensitivity of the models developed.

Censor statistics were highlighted in the study since, when performing a study for a designated period of time, any units that was still operational at the end of the study were referred to as time censored. Censor statistics were set at 0 for all the Weibull distribution analysis. It is important to note that the data collected during the study was not censored, meaning that it was all obtained within a designated one-year period. Time censoring is also known as Type I censoring on the right. Conversely, failure censoring occurs when conducting the study until a predetermined number of failures have been observed. The AD is a measure of how closely the data adheres to a specific distribution (Wisniewski, 2019). Table 3.1 presents the AD values for different distribution plots as indicated in Figures 3.2, 3.3, and 3.4.

In this study, when a particular distribution was applied to a given dataset and a smaller the AD statistic was seen, it then meant, the better the fit of the distribution to the data.

Table 3.1: The AD values for different distribution plots (Wisniewski, 2019)

Distribution	Anderson-Darling	P-value
Exponential	9.599	$p < 0.003$

Distribution	Anderson-Darling	P-value
Normal	0.641	$p < 0.089$
3-parameter Weibull	0.376	$p < 0.432$

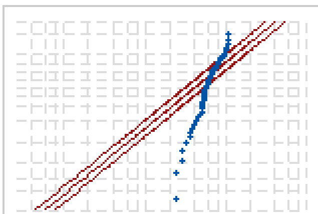


Figure 3.3: Exponential Distribution

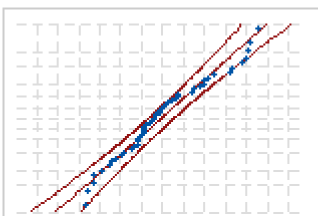


Figure 3.4: Normal Distribution

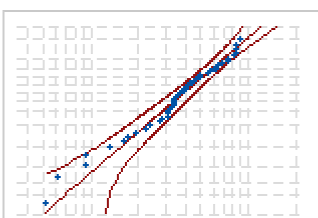


Figure 3.5: 3-parameter Weibull Distribution (Wisniewski, 2019)

Weibull distribution in reliability analysis entails a statistic that was named failure. It stands for the data size for the study. In this case, there were 1000 in number which represented the failure data size. The inter-quartile range (IQR) refers to the space between the first quartile (Q_1) and the third quartile (Q_3), with 50% of the data points falling within this range (Wisniewski, 2019). When it came to the large data or the unusual data, it is important to refer to IQR where the data that are unusually large lie outside the Q_1 and Q_3 limits. The median represents the middle value of the dataset. Half of the observations in the dataset are greater than the median and the other half are lesser. The standard deviation (StDev) is the most widely used measure of the spread, or dispersion, of the data around the mean (Wisniewski, 2019). The mean is the average value of the dataset, calculated by adding all the values and dividing by the number of observations.

The outcomes of the Weibull distribution included the probability density function, Survival function, hazard function, and Weibull probability plot. The hazard function analyzes the life distribution through historical failure data and online status monitoring data. The Probability density function is a way of describing the distribution function, with the parameters controlling the shape, scale, and location. The survival function is a function that calculates the likelihood of an object of interest, such as a device or patient, surviving past a certain point in time. The Weibull plot is a graphical method that determines if a dataset follows a 2-parameter Weibull distribution, with the location assumed to be zero. The Weibull plot utilizes special scales, and if the dataset indeed follows a Weibull distribution, the points then are linear or nearly linear. Additionally, the Weibull distribution is used to model reliability data and determine the percentage of items that are expected to fail during the burn-in period in terms of the machine's age. The probability plot provides insights into the expected time and scale of fast wear-out. The Weibull distribution and its associated functions provide valuable insights into system reliability and can be used to optimize maintenance schedules and predict failures, minimizing downtime and maintenance costs.

3.2.5 The procedure that was used to perform regression analysis to validate the models.

In line with step 9, Monte Carlo Simulation requires that the regression model equation is established and used as a transfer function during validation of results. In this situation equation 2.1 requires that's input data have the age and the number of failures recorded during the age of operation. Based on this all the input variables X_1 to X_{18} must explain the response variable Y (MTBF). Regression modeling, sensitivity analysis and validation of the simulated results requires input variables as well as the responses or the output variable and the R-square value should >= 0.7 (70%) and exceedingly as illustrated in appendix 4 (Wen et al., 2020). R-square >= to 70% implies that the value of the response is explained by all the variables in the model equation (Wen et al., 2020).

In summary, the methodology is such that it relies on survey design to highlight the critical departments in REAL. Furthermore, the method is used to depict the scenario of the maintenance strategy within the organization, indicating the most affected department. With the help of the real-time data equipment failure, a set of data that was analyzed using Monte Carlos was deduced. The generated data was used in the Weibull distribution analysis. The results from the analysis were presented in chapter four.

CHAPTER FOUR: RESULTS AND DISCUSSION

In this chapter, results and discussion are explored. The expected result of the study depends on the goals and the aim set in the objectives. Under the results sections, an evaluation of maintenance based on the age of the machine and the number of failures is done. This chapter further presents the criticality results alongside the Weibull distribution analysis.

4.1. Assessment of the criticality

Table 4.1 presents the assessments of the critical equipment. In this case, the score was determined using the mechanical and electrical failures of the machines in the weaving department.

Table 4.2: Failure Mode & Effects Analysis for Critical Equipment

Failure Mode & Effects Analysis (FMEA) Date: 11 April 2018 **Types of FMEA:** Process

Rivatex East Africa Limited (REAL) **Analysis:** Per Shift **Department:** Weaving

Failure Modes	**A. Severity** Rate 1-10: 10= Most Severe	**B. Probability of Occurrence** Rate 1-10: 10= Highest Probability	**C. Probability of Detection** Rate 1-10: 10= Lowest Probability	**D. Risk Priority Number (RPN)** D=A*B*C
Yarn Winding Machine				
Mechanical Failure	2	3	2	12
Electrical Failures	3	4	1	12
Total				**24**
Yarn Warping Machine				
Mechanical Failure	2	2	2	8
Electrical Failures	3	4	1	12
Total				**20**
Sizing machine				
Mechanical Failure	4	5	3	60
Electrical Failures	4	3	1	12
Total				**72**
Looms				
Mechanical Failure	6	7	2	84
Electrical Failures	4	5	2	40
Total				**124**

According to the results of critical assessment of equipment in the weaving section shown in Table 4.1, the Yarn Winding Machine had a value of 24; the Yarn Warping Machine had a value of 20, the Sizing machine had a value of 72, and the Looms had a value of 124. It was established from the results that the looms are critical equipment. From the criticality assessment of REAL production departments, the weaving section posted the highest score indicating that the section has some notable number failures as far as maintenance activities are concerned. In this regard, the modeling of the maintenance in the weaving department was performed to assess the maintenance strategy used and to analyze the failure data to come up with an optimized maintenance strategy. The assertion made is corroborated by additional studies conducted by Sarih et al. (2018) and Shahin et al. (2020).

4.2 Modeling of the Maintenance strategy in the Critical Department

Figure 4.1 shows a fish-bone diagram that presents the maintenance strategy results based on the fish-bone diagram assessment. The diagram is based on the data that was collected using questionnaires and observation of the maintenance activities at the facility. During the data collection, the factors that contributed to most failures were recorded and assessed in relation to the nature of maintenance that followed once a failure occurred in the critical department.

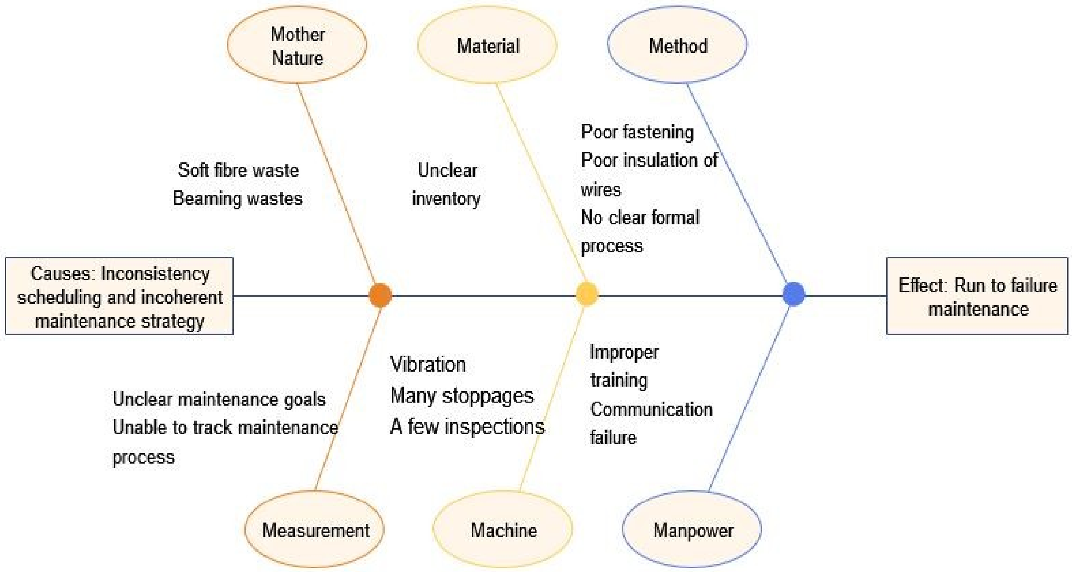


Figure 4.2: Fishbone diagram indicating the nature of dominant maintenance strategy.

The over-reliance on run-to-failure maintenance or breakdown maintenance strategy is a major problem due to the inconsistency and incoherence of preventive maintenance strategy as illustrated in Figure 4.1. It has been observed that failures occur due to various reasons such as machine vibrations, many stoppages, and a few inspections. The fish-bone diagram developed to identify the causes of failures also highlighted poor installation of wires, poor fastening, and the absence of a clear formal process as method/ strategy issues. Additionally, having unclear inventory was identified as a materials problem. Communication failure and improper training were attributed to man, while soft fibers choking, and beam wastes were attributed to Mother Nature. The inability to track maintenance processes and unclear maintenance goals were identified as measurement issues. Therefore, it is important to address these underlying issues and adopt a more proactive preventive maintenance approach to ensure optimal machine performance and avoid unplanned downtime. Ershadi et al. (2018) conducted studies that are consistent with the observed findings, suggesting a consensus among multiple sources.

4.3 Monte Carlo simulation analysis

Monte Carlo simulation entails Weibull distribution analysis was performed on the maintenance time collected from the systems on the critical machines. To determine the shape, scale parameters, and minimum age value of a system based on Weibull distribution for Monte Carlo simulation, equation 3.2 was utilized. Following this, equation 3.3 is used to undertake 1000 iterations of Monte Carlo simulation using real-time data collected in REAL. The data set includes 6 system components from rapier weaving machines, 7 system components from airjet weaving machines and 2 common lubrication points. Other parameters examined were total time data, number of failure data, and calculated MTBF. These Figures in appendix 5 exhibits the probability density function, Weibull distribution, survival function, and hazard function alongside shape, scale, mean STDev, median, IQR, failure data size, censor, and AD. These metrics are crucial in evaluating the availability and maintainability of the systems, and the findings were used to optimize maintenance schedules, predict component failures, and minimize downtime. The use of Monte Carlo simulation and Weibull distribution allows for accurate probabilistic modeling and prediction of system failures.

4.3.1 Weibull distribution analysis

The data generated during Monte Carlo simulation analysis, as presented in Appendix 5, was subjected to Weibull analysis. Figures 1 to 19 in the appendix were utilized for this purpose. The results of the analysis were discussed in detail. The Weibull analysis entails the shape and scale parameters displayed with the respective AD value. The analysis presents the shape and scale parameters since it follows a 2-parameter Weibull distribution. The relationship between the Weibull distribution parameters, hazard functions, and reliability functions is based on the shape parameters. By adjusting the shape parameters, several characteristics of the maintenance times can be modeled for different life distributions. The Weibull distribution results were illustrated in Figures 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8 and 4.9. The analysis included several key outcomes, such as the Probability density function, which provides an estimate of the likelihood of a failure occurring at a given time. Additionally, the survival function was calculated, which represents the probability that an item will survive beyond a certain point in time. The hazard function was also evaluated, which provides insights into the rate of failure over time.

Moreover, the Weibull probability plot was utilized, which is a graphical tool that helps to visualize the distribution of failure times. The results of the analysis presented not only the failure times but also the rate of failure, which can provide valuable information for predicting when future failures may occur. This assertion is also reported by other studies by Zulkafli & Mat Dan (2016). The two parameters of the Weibull distribution were also identified, allowing for a more complete understanding of the data. Lastly, the history of failure for each dataset was examined, providing insights into the underlying causes of the failures and potential avenues for future improvements.

4.3.2 Effects of selected parameters on systems components

The analysis of failures was conducted by examining the data collected in terms of the age of the machine versus the number of failures. Probability plots were employed to accomplish this task, and the Weibull distribution was used to determine the shape and scale of the data. For detailed information, please refer to Appendix 5. In this case, the Weibull distribution was considered as a model for a linearly increasing failure rate. In Figure 4.2, system component X_9 had the highest value of 2418.89 for the shape parameter, while system component X_1 had the lower value of 0.962948. The optimal value was determined to be 1.46503, suggesting that the machines underwent early-life wear and failures.

4.3.2.1 Effects of shape parameters on systems components

Figure 4.2 showcased the plots depicting the shape parameters for each system component. In contrast, the system component X_{16} had the highest scale parameter value of 24873.2 hours, while system component X_{18} had the lowest value of 4.426714 hours. However, the optimal value range of 1231.69 to 1683.46 was obtained through the assessment of the response, MTBF. As the shape value surpasses 1.46503 throughout the products' lifespan, the risk of wear-out failures steadily increases. This assertion finds support in additional studies conducted by Marcello (2020) and Da Silva et al. (2020), further validating its significance.

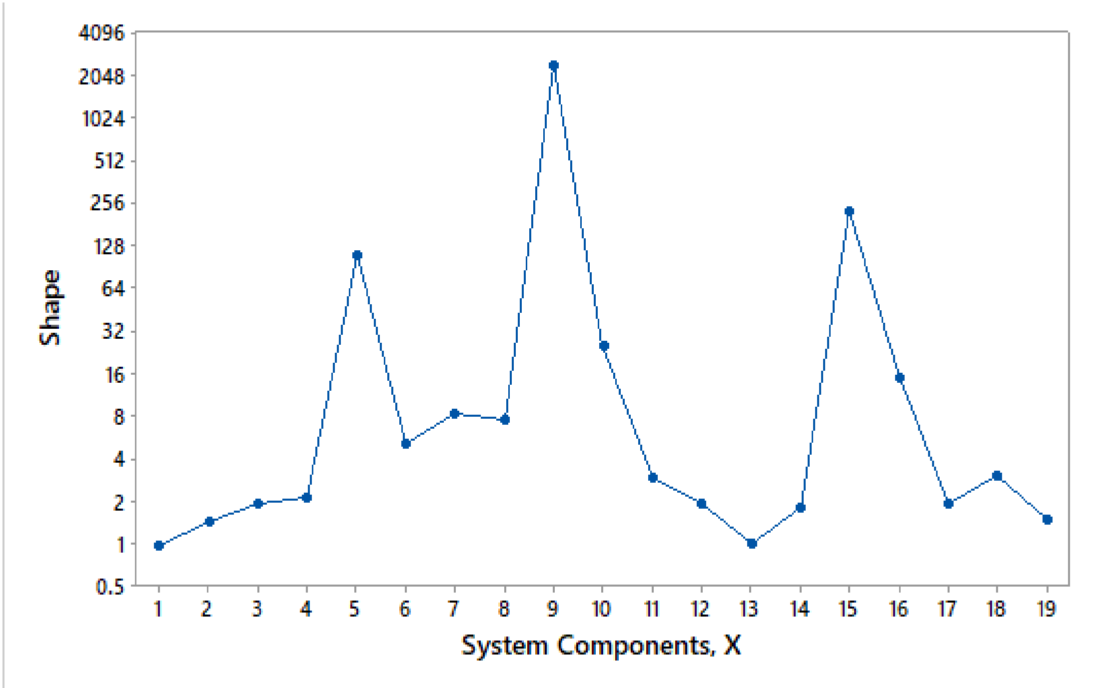


Figure 4.2: Shape parameter comparison chart

4.3.2.2 Effects of scale parameters on Systems Components

Figure 4.3 illustrated the scale parameters corresponding to each system component of the critical equipment. It became evident that the machines could not surpass the 1683.46-hour mark without encountering rapid deterioration of worn-out parts. From Figure 4.3, it was observed that the selvedge formation system in the rapier weaving machine suffered from fast wear-out failures during the final period of its product life, requiring preventive operations approximately every 2195.58 hours. Similarly, the lubrication fabric take-up and let-off systems in both the airjet and rapier weaving machines led to very fast wear-out failures, necessitating preventive operations every 1231.69 hours.

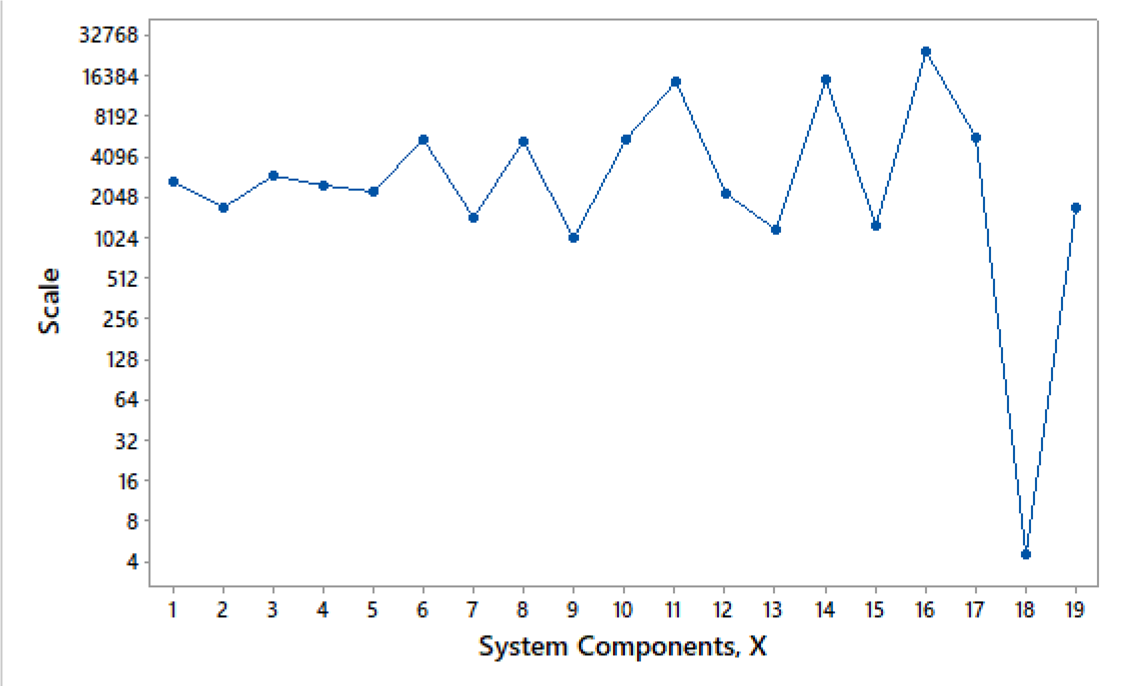


Figure 4.3: Scale parameter comparison chart

Furthermore, system components such as the reed system, warp let-off system, and fabric take-up system experienced very fast wear-out failures during the final period of their product life. Therefore, the optimal hours for operations before the next maintenance operation was carried out ranged from 1231.69 to 1683.46 hours as a preventive measure. As reported by Pena et al. (2022), the hazard function described a slow but increasing failure rate, with the largest increase occurring toward the end of the equipment's life, indicating the need for more preventive maintenance measures within the 1231.69 and 1683.46-hour range.

4.3.2.3 Effects of Mean parameters on systems components

Figure 4.4 depicted the plot showcasing the means across the system components, facilitating a comprehensive comparison of the system breakdown hours. The highest mean, recorded at 24011.5 hours, belonged to system component X_{16}, while the lowest mean, measured at 3.81269 hours, corresponded to X_{18}. Consequently, the optimal mean failure time was determined to be 1524.30 hours. Any data that fell outside of these limits could potentially indicate inconsistent and unreliable outcomes of the preventive maintenance strategy.

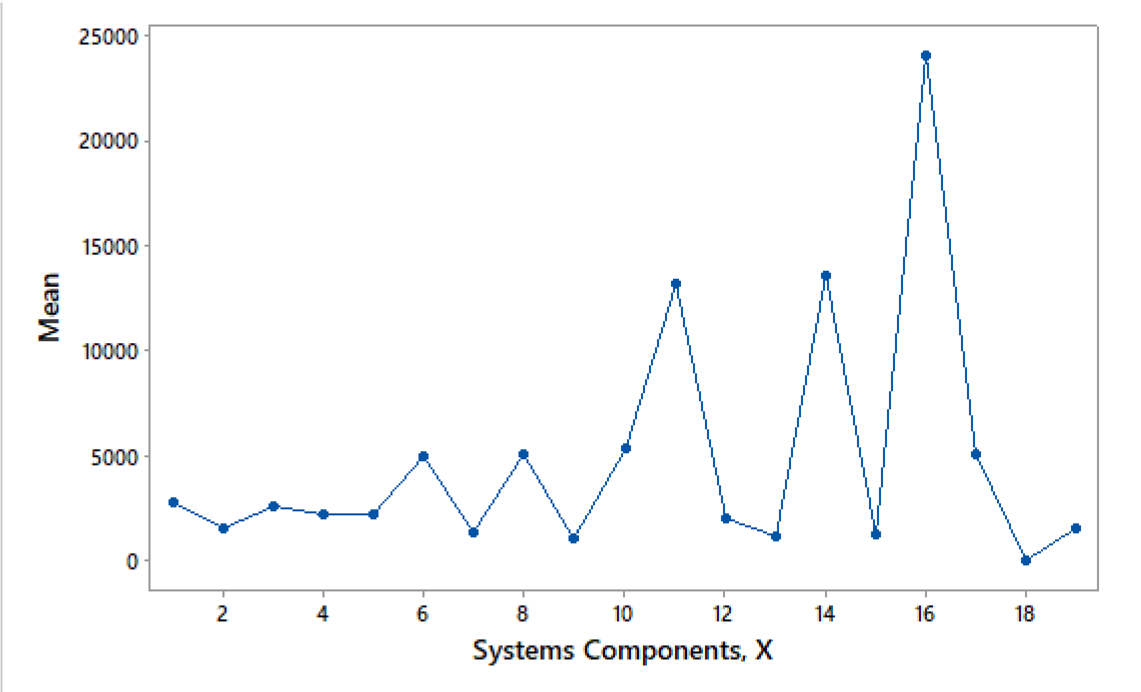


Figure 4.4: Mean parameter comparison chart

4.3.2.4 Effects of STDev parameter on Systems Components

Figure 4.5 presented a plot illustrating the STDev parameter for all system components, allowing for convenient comparison. Among the system components, the highest STDev value was recorded for X_{14}, reaching 7643.126, while the lowest STDev value was observed for X_9, measuring 0.530333. Consequently, the optimal value for the STDev parameter was determined to be 1057.73 hours.

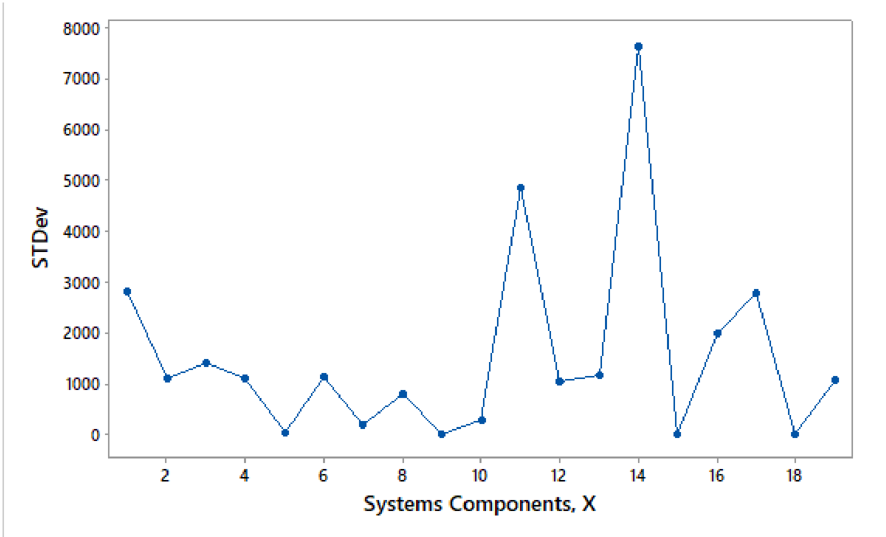


Figure 4.5: STDev parameter comparison chart

4.3.2.5 Effects of Median parameter on systems components

Figure 4.6 displayed a plot representing the Median parameter for each system component, enabling convenient comparisons to be made. Within the system components, the highest median value was recorded for X_{16}, reaching 24266.8 hours, while the lowest median value was found for X_{18} at 3.78242 hours. Subsequently, the optimal median failure time was determined to be 1310.85 hours, with a corresponding standard deviation of 1057.73 hours.

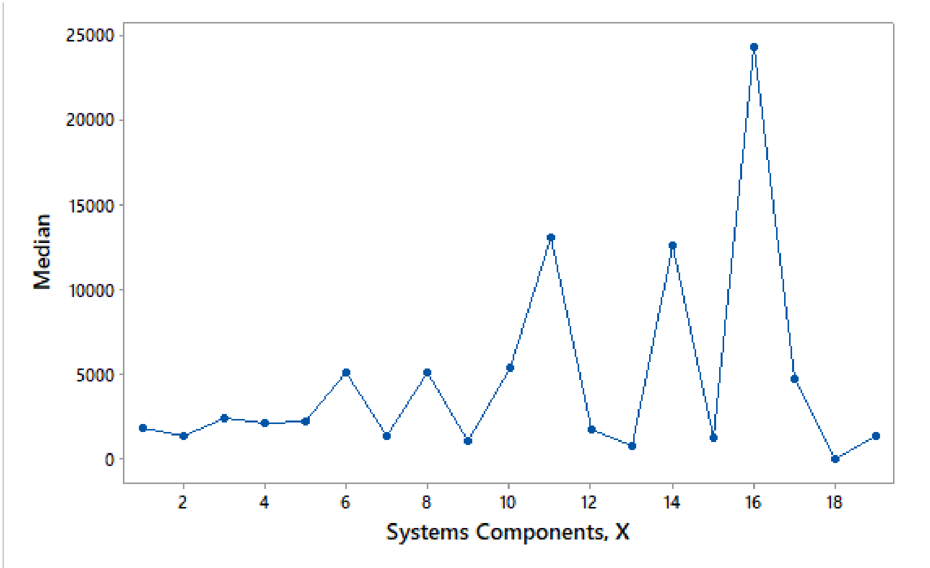


Figure 4.6: Median parameter comparison chart

4.3.2.6 Effects of IQR parameters on systems components

Figure 4.7 showcased a plot illustrating the IQR parameters for each system component, facilitating comparisons for analysis. Among the system components, the highest IQR value was observed for X14, reaching 10477.9, while the lowest IQR value was found for X9 at 0.650468. The optimal IQR, calculated between the first and third quartiles (Q_1 and Q_3), was determined to be 1384.70 hours. This value provides valuable insight into the survival rate of the component. It is important to note that Q3 from the IQR marks the point at which wear increases, eventually leading to failures of machine components.

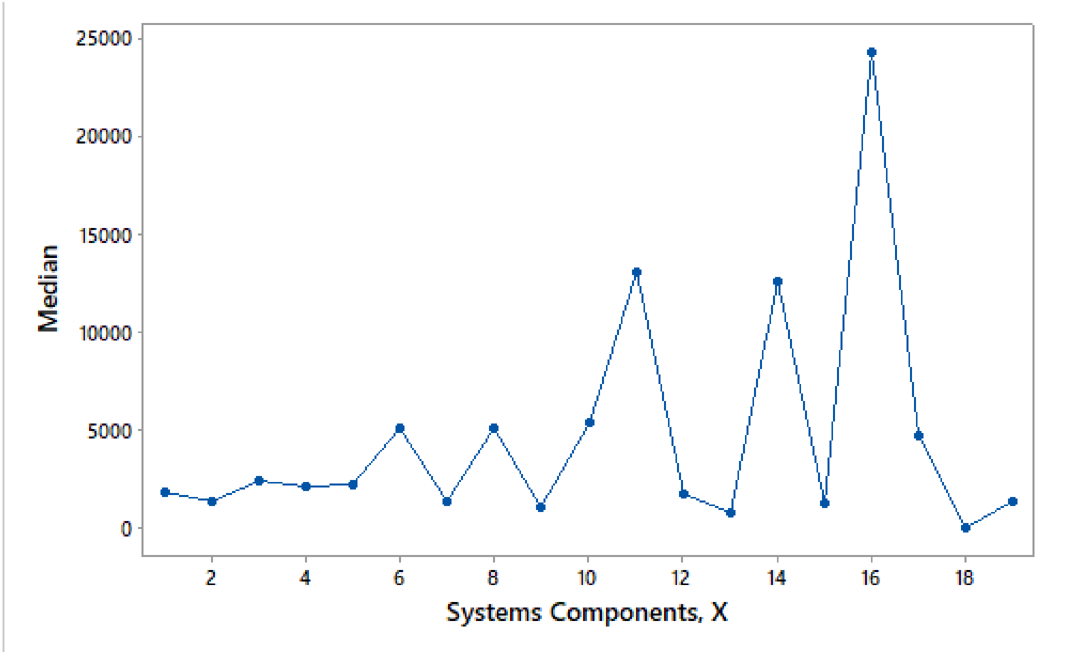


Figure 4.7: IQR parameter comparison chart

4.3.2.7 Effects of AD parameters on systems components

Figure 4.8 presented a plot illustrating the AD (Anderson-Darling) parameters for each system component. The AD values =< 0.376 indicated that the data fit a Weibull distribution, implying that failures followed this distribution pattern. AD values > 0.376 indicated that, failures persisted until the maintenance team was able to address and handle the machines appropriately.

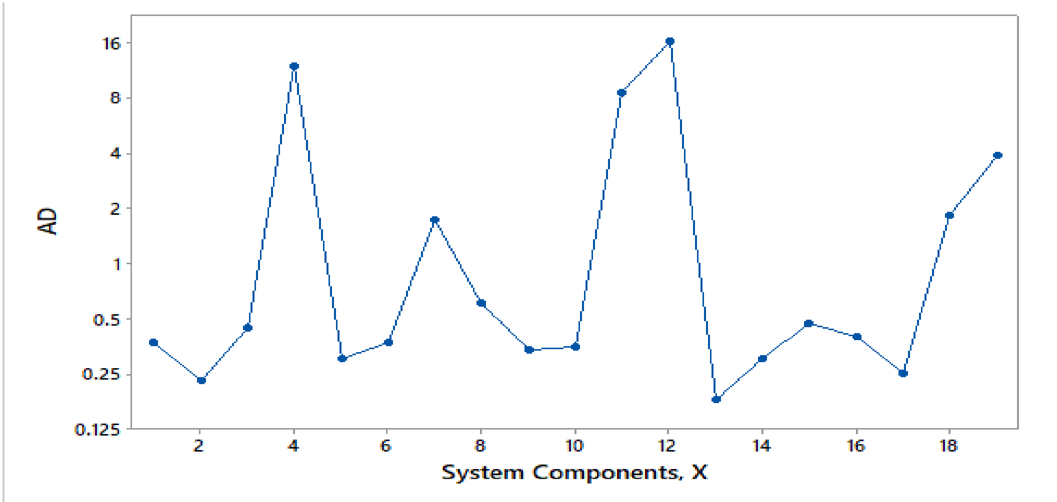


Figure 4.8: Comparison of AD values of system components

4.3.3 Analysis of MTBF

Figure 4.9 illustrates the probability density function, Weibull plot, hazard function, and survival function of the responses for MTBF.

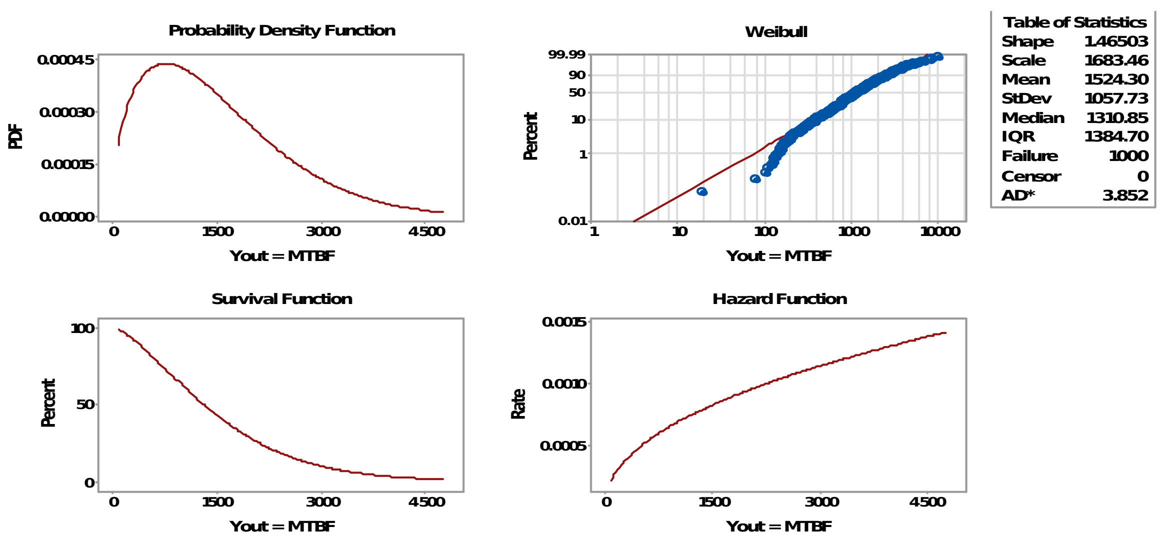


Figure 4.9: Distribution and probability Plot for Response, MTBF

Figure 4.9 portrayed the shape parameter for the systems as 1.46503, with a scale value of 1683.46. Notably, a shape value of 1.46503 suggests that most failures are attributable to early wear-out failure, indicating the presence of premature failures upon machine installation. The unusual values observed in system components X_4, X_{11}, and X_{12} indicate inconsistencies in the approach, resulting in lengthy maintenance intervals that do not align with preferred maintenance practices. Pena et al. (2022) reported that some early wear-out failures stem from the utilization of low-quality parts and substandard installation procedures. A shape value equal to or greater than 1.46503 signifies an increasing failure rate during the initial stages of operation. However, the lower limit of shape parameter reveals the actual maintenance scenario and failure model at REAL. Consequently, the average Mean Time Between Failures (MTBF) amounts to 1471.05 hours. The survival function indicates that the system components exhibit a 50% survival rate at 1683.46 hours.

4.4 Results of system data analysis

The validation of results obtained from Monte Carlo simulation was a critical step in assessing the reliability and maintenance requirements of critical equipment. In this study, validation was achieved using regression analysis, where input parameters were established using Monte Carlo simulation, Weibull distribution, and probability analysis. The regression model demonstrated a strong relationship (R-square = 85.56%) between 18 input variables and the mean time between failures (MTBF). A sensitivity analysis was conducted to rank the variables based on their influence on the MTBF. Variables with significant influence required proper maintenance, while those with lesser influence indicated good maintenance practices. These findings were supported by previous studies.

4.4.1 Validation of the Results from Monte Carlos simulation

From the critical equipment, the input parameters were established as the system components that are prone to failure and are subject to maintenance activities. In this case, all the input variables were obtained following the Monte Carlos simulation and Weibull distribution and probability analysis. In the simulation, 1000 random dataset were established for each input variable. The model equation is used to calculate simulated outcomes as used by Wisniewski (2019). From the X_1 to X_{18} input variables and Y which are the response variables, the model equation 4.5 was obtained.

The deduced regression equation was as follows;

$$Y = -17267 + 0.00712\,X_1 + 0.0104\,X_2 + 0.01112\,X_3 - 0.0206\,X_4 - 1.001\,X_5 - 0.0124\,X_6 - 0.0288\,X_7 - 0.0298\,X_8 + 20.3\,X_9 + 0.0548\,X_{10} - 0.00259\,X_{11} - 0.0144\,X_{12} + 0.0105\,X_{13} - 0.00161\,X_{14} + 0.51\,X_{15} + 0.00154\,X_{16} + 0.30017\,X_{17} - 398.04\,X_{18} \qquad 4.5$$

The value of R square was 85.56% which implies that the variation in Y (MTBF) is a result of the entire input variables. Therefore, the model explains all the variability of the response data around its mean. The same assertion is documented in additional studies by Marcello (2020) and Da Silva et al. (2020). For instance, 1683.46 hours is the mean time between failures; therefore, there should be a preventive maintenance activity once in this duration on the various systems before the anticipated breakdown occurs.

4.4.2 The influence of the input variable on the output MTBF

A sensitivity analysis was conducted on the regression model to determine the degree of influence of each variable on the response. The descending order to influence that the input variable has on the output (MTBF) variable is in the following order: Number of failures (both), selvedge formation system (rapier), reed system (air-jet), machine main drive system(rapier), connectivity system (rapier), harness frames system (air-jet), machine drive system (air-jet), lubrication main drive (both), connectivity system (air-jet), reed system (rapier), warp let-off system(rapier), selvedge formation system (air-jet), fabric take-up system (rapier), fabric take-up system (air-jet), total time (both), lubrication fabric take-up (both) and let off and lastly warp let-off system (air-jet).

The variation on the contribution of each input variable on the influence it has on the MTBF is a result of the contribution each variable has on the number of failures recorded in the critical equipment. The number of failures recorded in each system significantly impacts on the output variables while warp let-off system on air-jet has fewer influences. Those variables with less influence imply that they are under proper maintenance, while systems such as the selvedge formation system on rapier machines have poor maintenance due to increased failures. Other studies, such as Mostafa et al. (2015) and Li et al. (2016), have also reported the same assertion.

4.4.3 The effects of the arrangement sequence of input variables on the MTBF

The results of the Model Building Sequence and the incremental effects of input variables demonstrated a statistically significant relationship between the Y and X variables in the models, with a significance level of $P<0.10$, as shown in Appendix 6. Similarly, the model building process and inclusion of specific x variables demonstrate a notable increase in the R-square value. For example, when considering variables X_1, X_9, X_{11}, X_{17}, and X_{18}, the regression model explains a substantial 95.67% of the variation observed in the output variable Y.

Table 4.2 Variation in MTBF due to input variables

R^2	95.5	95.67	95.64	95.52	95.63	95.43	95.52	95.63
	Model building sequence and incremental impact of X variables							
X_1	95.50(3)	95.67(4)				95.43(3)		
X_2	95.50(4)							
X_3	95.50(5)							
X_4							95.52(5)	
X_5							95.52(4)	
X_6							95.52(3)	
X_7				95.52 (3)				
X_8				95.52 (5)				
X_9		95.67(5)		95.52(4)				
X_{10}			95.64 (4)					
X_{11}		95.67(3)	95.64(3)					
X_{12}			95.64(5)					
X_{13}								95.63(4)
X_{14}					95.63(3)			
X_{15}								95.63(3)
X_{16}								
X_{17}	55 (1)	55 (1)	55(1)	55 (1)	55 (1)	55 (1)	55 (1)	55 (1)
X_{18}	80 (2)	80 (2)	80(2)	80 (2)	80 (2)	80 (2)	80 (2)	80 (2)

It was established that all the input variables had a significant impact on the variation of MTBF, as evident in Table 4.2. The response variable, MTBF, was found to be influenced by X_1 to X_{18} in the regression model, with an R-Squared value greater than 95%. This observation indicated that all the variables were responsible for the variance in MTBF. In essence, this was done to validate the impact the variables have on the response. Additionally, there were large residuals and unusual input values in the data, which suggested failures occurring at the extreme age of the machine. As noted by previous studies by ÖzcAn et al. (2020), the presence of large residual values of input variables also strongly influenced the model. Furthermore, ÖzcAn et al. (2020) also found that the presence of large residual values and unusual input values in the data implied that there were issues with the timing and frequency of maintenance activities that were impacting the performance of the system. Such inconsistencies implied issues with the maintenance strategy, incoherent schedules, and unscheduled downtime, which may have contributed to the presence of the large residuals.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study aimed to establish an effective maintenance schedule and parameters for critical equipment in the weaving section of REAL's textile manufacturing processes. To achieve this, three specific objectives were identified. Firstly, data on failures and their frequency in the weaving section were collected. Secondly, a model was developed to predict maintenance timing and component failures. Finally, system data was analyzed to optimize the maintenance schedule and parameters for the critical equipment. By fulfilling these objectives, the study aimed to enhance efficiency, minimize downtime, and maintain smooth operations in the weaving section.

1. The most critical equipment was the loom, with the highest risk priority number score of 124, while the Yarn Warping Machine had the lowest score of 20.

2. The mapping out of critical equipment revealed an over-reliance on run-to-failure maintenance and identified inconsistencies and incoherence in the preventive maintenance strategy, highlighting the importance of addressing issues like poor installation, unclear inventory, communication failures, and improper training. Consequently, a proactive maintenance approach is necessary to optimize machine performance and minimize unplanned downtime.

3. The Monte Carlo simulation and Weibull distribution analysis yielded valuable findings regarding the maintenance requirements and failure patterns of critical equipment, which facilitated the optimization of maintenance schedules, prediction of component failures, and reduction of downtime. The shape parameter of 1.46503 obtained indicated early wear-out failures, and an optimal maintenance schedule range of 1231.69 to 1683.46 hours was determined.

4. The validation of results obtained from Monte Carlo simulation through regression analysis showed a strong relationship (R-square = 85.56%) between input variables and mean time between failures (MTBF), indicating the influence of various system components on maintenance requirements.

5. A sensitivity analysis ranked the variables based on their influence on MTBF, indicating the need for proper maintenance for variables such as X_{17} and X_{18} with significant influence.

6. The arrangement sequence of input variables further demonstrated a statistically significant relationship, with specific variables increasing the R-square value and explaining a substantial portion of up to 95.67% of the variation in MTBF.

7. The presence of large residuals and unusual input values suggested issues with maintenance strategy and schedules, impacting system performance. AD values $\leq$ 0.376 indicated Weibull distribution fit, while AD values > 0.376 implied persistent failures until addressed by the maintenance team.

5.2 Recommendations

5.2.1 Guidelines for Efficient Operations and Maintenance of Weaving Section

1. The maintenance team should engage in gathering information on each machine. The repairs and parts replacement should be invoked by a maintenance guideline obtained from the document with the model and serial numbers of the parts.
2. A baseline should be developed on machine usage, for instance, the machine downtime, amount of time spent by the technicians, amount of time between repairs, and technician's response time in the preventive maintenance program.

3. The technician should maintain a preventive maintenance checklist that helps in estimating the amount of time needed in a particular machine.
4. Cleaning of the machine should be done using a brush as opposed to blowing air to the parts.
5. Big data is beginning to play a more significant part in machine maintenance and can improve performance. The strategy is advised for REAL to set up preventative maintenance routines that lower downtime and save money on maintenance. Big data serves as a foundation for increasing equipment lifespan, minimizing needless preventive maintenance, and streamlining spare part inventories.
6. Condition-Based Maintenance monitoring technique needs to be employed by employees with the aim of keeping a close eye on the vibrations, oil, electrical circuit, and pressure for analysis.
7. Develop an efficient maintenance schedule for the machines by deploying parts and technicians at the locations on time.
8. Engage in continuous training of technicians in order to increase their efficiency and equip them with necessary skills.
9. Establish maintenance procedures for repairs. Furthermore, a list of internal and outsourced maintenance tools should be prepared. A review of the well-grounded inventory and servicing of the machines should be done on a weekly, monthly, quarterly, semi-annual, and annual basis.
10. Prioritize maintenance operations, breakdown maintenance, and services should be scheduled on annual or bi-annual intervals. Routine maintenance practices can be categorized as high, medium, and low priority tasks.

11. Develop consistency in the inspection as an ongoing project and avoid skipping the routine.
12. Always seek improvements as far as maintenance procedures and plans are concerned.
13. An ICT should be on boarded into the maintenance team in order to handle the connection and the programming of the connectivity system.

5.2.2 Proposed Areas for Future Research

1. Finally, the study recommends conducting further research on the scheduling of maintenance activities for industrial equipment, particularly focusing on aspects that are not related to maintenance management strategies. By exploring situations such as unplanned, reactive maintenance, preventive maintenance, and predictive monitoring, this research can provide valuable insights and contribute to the development of more comprehensive and effective maintenance scheduling approaches.
2. Additionally, it is recommended to conduct a future study on the relationship between optimized time schedules and production per shift specifically for jigger dyeing machines. By investigating the impact of various time schedules on production efficiency, this research can offer valuable insights into optimizing scheduling strategies for enhanced productivity in jigger dyeing operations.

REFERENCES

Andrade, Y., Cardenas, L., Viacava, G., Raymundo, C., & Dominguez, F. (2020). Lean manufacturing model for the reduction of production times and reduction of the returns of defective items in textile industry. In Advances in Design for Inclusion: Proceedings of the AHFE 2019 International Conference on Design for Inclusion and the AHFE 2019 International Conference on Human Factors for Apparel and Textile Engineering, July 24-28, 2019, Washington DC, USA 10 (pp. 387-398). Springer International Publishing.

Chan, D., & Mo, J. (2017). Life Cycle Reliability and Maintenance Analyses of Wind Turbines. *Energy Procedia*, 328-333.

Chopra, A., Sachdeva, A., & Bhardwaj, A. (2014). General Maintenance Scenario in Indian Process Industry. *International Journal of Research in Management, Science & Technology (E-ISSN: 2321 -3264)*.

Da Silva, E. T., & Piratelli, C. L. (2020). Strategic formulation of industrial maintenance based on equipment reliability in a sugar and ethanol production plant. Independent Journal of Management & Production, 11(7), 2592-2612.

Duer, S., Woźniak, M., Paś, J., Zajkowski, K., Bernatowicz, D., Ostrowski, A., & Budniak, Z. (2023). Reliability Testing of Wind Farm Devices Based on the Mean Time between Failures (MTBF). Energies, 16(4), 1659.

Endrenyi, J., Aboresheid, S., Allan, R. N., Anders, G. J., Asgarpoor, S., Billinton, R., . . . Schneider, A. (2001). The Present Status of Maintenance Strategies and the Impact of Maintenance on Reliability. *IEEE Transactions On Power Systems, VOL. 16, NO. 4*, 638-643.

Ershadi, M. J., Aiasi, R., & Kazemi, S. (2018). Root cause analysis in quality problem solving of research information systems: a case study. International Journal of Productivity and Quality Management, 24(2), 284-299.

Fan, J., & Li, Z. (2020, February). Study on Mean Time Between Failures Prediction Algorithms Based on Weibull Distribution. In IOP Conference Series: Earth and Environmental Science (Vol. 440, No. 2, p. 022083). IOP Publishing.

Fithri, P., Andra, D. J., & Wirdianto, E. (2020, May). The use of FMEA for the Quality Control Analysis of Greige Fabrics (case study in the Weaving Department of PT. Unitex, Tbk). In IOP Conference Series: Materials Science and Engineering (Vol. 847, No. 1, p. 012002). IOP Publishing.

Fredriksson, G., & Larsson, H. (2012). An analysis of maintenance strategies and development of a model for strategy formulation - A case study. 16-68.

Gupta, G., & Mishra, R. P. (2016). A SWOT analysis of reliability-centered maintenance framework. *Journal of Quality in Maintenance Engineering 22, no. 2*, 130-145.

Gupta, V., & Gupta, P. (2020). Digitization of Textile Manufacturing Process: An Exploration. Supply Chain Pulse, 11(1), 24-30.

He, Z., Tran, K. P., Thomassey, S., Zeng, X., Xu, J., & Haiyi, C. (2020). A deep reinforcement learning based multi-criteria decision support system for textile manufacturing process optimization. arXiv preprint arXiv:2012.14794.

Heiser, T., & Hofmeister, J. P. (2019, May). Bathtub, Failure Distribution, MTBF, MTTF, and More: They are Related. In MFPT Conference, King of Prussia, PA (pp. 14-16).

Hiruta, T., Uchida, T., Yuda, S., & Umeda, Y. (2019). A design method of data analytics process for condition based maintenance. CIRP Annals, 68(1), 145-148.

Holgado, M., Macchi, M., & Evans, S. (2020). Exploring the impacts and contributions of maintenance function for sustainable manufacturing. International Journal of Production Research, 58(23), 7292-7310.

Huynh, N. T. (2020). Online defect prognostic model for textile manufacturing. Resources, Conservation and Recycling, 161, 104910.

Ilangkumaran, M., & Kumanan, S. (2009). Selection of maintenance policy for textile industry using hybrid multi-criteria decision-making approach. *Journal of Manufacturing Technology Management 20(7)*, 1009-1022.

Islam, M. M., Perry, P., & Gill, S. (2021). Mapping environmentally sustainable practices in textiles, apparel and fashion industries: a systematic literature review. Journal of Fashion Marketing and Management: An International Journal, 25(2), 331-353.

Jäntschi, L., & Bolboacă, S. D. (2018). Computation of probability associated with Anderson–Darling statistic. Mathematics, 6(6), 88.

Jia, F., Yin, S., Chen, L., & Chen, X. (2020). The circular economy in the textile and apparel industry: A systematic literature review. Journal of Cleaner Production, 259, 120728.

Li, H., Deloux, E., & Dieulle, L. (2016). A condition-based maintenance policy for multi-component systems with Lévy copulas dependence. *Reliability Engineering & System Safety 149*, 44-55.

Li, J., Collins, G., & Govindarajulu, R. (2019). System reliability growth analysis during warranty. International Journal of Mathematical, Engineering and Management Sciences, 4(1), 85-94.

Liu, N., Chow, P. S., & Zhao, H. (2020). Challenges and critical successful factors for apparel mass customization operations: recent development and case study. Annals of Operations Research, 291, 531-563.

Mahfoud, H., Barkany, A. E., & Biyaali, A. E. (2016). Preventive maintenance optimization in healthcare domain: status of research and perspective. *Journal of Quality and Reliability Engineering 2016*.

Mahlangu, B., & Kruger, L. (2015). The impact of the maintenance management system: A case study of the PetroSA GTL refinery. *South African Journal of Industrial Engineering*

Mahmood, A. (2020). Smart lean in ring spinning—a case study to improve performance of yarn manufacturing process. The Journal of The Textile Institute, 111(11), 1681-1696.

Marcello, B., Davide, C., Marco, F., Roberto, G., Leonardo, M., & Luca, P. (2020). An ensemble-learning model for failure rate prediction. Procedia Manufacturing, 42, 41-48.

McLaren, D., Niskanen, J., & Anshelm, J. (2020). Reconfiguring repair: Contested politics and values of repair challenge instrumental discourses found in circular economies literature. Resources, Conservation & Recycling: X, 8, 100046.

Mehta, P., Werner, A., & Mears, L. (2015). Condition-based maintenance-systems integration and intelligence using Bayesian classification and sensor fusion. *Journal of Intelligent Manufacturing 26, no. 2*, 331-346.

Mostafa, S., Dumrak, J., & Soltan, H. (2015). Lean maintenance roadmap. *Procedia Manufacturing 2*, 434-444.

Nakagawa, T. (2006). *Maintenance Theory of Reliability.* Springer Science & Business Media.

Nguyen, K. T., Do, P., Huynh, K. T., Bérenguer, C., & Grall, A. (2019). Joint optimization of monitoring quality and replacement decisions in condition-based maintenance. Reliability Engineering & System Safety, 189, 177-195.

Orošnjak, M., Delić, M., & Ramos, S. (2022). Influence of Maintenance Practice on MTBF of Industrial and Mobile Hydraulic Failures: A West Balkan Study. In Machine and Industrial Design in Mechanical Engineering: Proceedings of KOD 2021 (pp. 617-625). Cham: Springer International Publishing.

ÖzcAn, E., DAnışAn, T., YumuşAk, R., & Eren, T. (2020). An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants. Eksploatacja i Niezawodność, 22(3).

Pal, K. (2020). Internet of things and blockchain technology in apparel manufacturing supply chain data management. Procedia Computer Science, 170, 450-457.

Parvin, F., Islam, S., Akm, S. I., Urmy, Z., & Ahmed, S. (2020). A study on the solutions of environment pollutions and worker's health problems caused by textile manufacturing operations. Biomed. J. Sci. Tech. Res, 28, 21831-21844.

Patten, M. L. (2016). *Questionnaire research: A practical guide.* . Routledge.

Peng, K. (2016). *Equipment management in the post-maintenance era: a new alternative to Total Productive Maintenance (TPM).* Productivity Press.

Piqueras, R., & Fernandez-Crehuet, J. M. (2019). Data analysis for the preventive maintenance of machinery. *Studies in Engineering and Technology*, *7*(1), 1.

Prasad, M. M., Dhiyaneswari, J. M., Jamaan, J. R., Mythreyan, S., & Sutharsan, S. M. (2020). A framework for lean manufacturing implementation in Indian textile industry. Materials today: proceedings, 33, 2986-2995.

Pride, A. (2016, 9 11). *Reliability-Centered Maintenance (RCM)*.

Rasmekomen, N., & Parlikad, A. K. (2016). Condition-based maintenance of multi-component systems with degradation state-rate interactions. *Reliability Engineering & System Safety 148*, 1-10.

Realyvásquez-Vargas, A., Arredondo-Soto, K. C., García-Alcaraz, J. L., & Macías, E. J. (2020). Improving a manufacturing process using the 8ds method. A case study in a manufacturing company. Applied Sciences, 10(7), 2433.

Saggiomo, M., Loehrer, M., Kerpen, D., Lemm, J., & Gloy, Y. S. (2016, January). Human-and task-centered assistance systems in production processes of the textile industry: determination of operator-critical weaving machine components for AR-prototype development. In 2016 49th Hawaii International Conference on System Sciences (HICSS) (pp. 560-568). IEEE.

Sarı, T., Güleş, H. K., & Yiğitol, B. (2020). Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry. Advances in Production Engineering & Management, 15(1), 57-68.

Sarih, H., Tchangani, A., Medjaher, K., & Pere, E. (2018). Critical components identification based on experience feedback data in the framework of PHM. IFAC-PapersOnLine, 51(11), 429-434.

Schmidt, B., Galar, D., & Wang, L. (2016). Context-awareness in predictive maintenance." In Current trends in reliability, availability, maintainability, and safety. *Springer, Cham*, 197-211.

Scime, L., Siddel, D., Baird, S., & Paquit, V. (2020). Layer-wise anomaly detection and classification for powder bed additive manufacturing processes: A machine-agnostic algorithm for real-time pixel-wise semantic segmentation. Additive Manufacturing, 36, 101453.

Shafiee, M., & Sørensen, J. D. (2019). Maintenance optimization and inspection planning of wind energy assets: Models, methods and strategies. Reliability Engineering & System Safety, 192, 105993.

Shahin, A., Labib, A., Haj Shirmohammadi, A., & Balouei Jamkhaneh, H. (2020). Developing a 3D decision-making grid based on failure modes and effects analysis with a case study in the steel industry. *International Journal of Quality & Reliability Management*, *38*(2), 628-645.

Shirvanimoghaddam, K., Motamed, B., Ramakrishna, S., & Naebe, M. (2020). Death by waste: Fashion and textile circular economy case. Science of The Total Environment, 718, 137317.

Uddin, F. (2019). Introductory chapter: Textile manufacturing processes. Textile Manufacturing Processes.

Vasili, M., Hong, T. S., Ismail, N., & Vasili, M. (2011). Maintenance optimization models: a review and analysis. *Proceedings of the 2011 International Conference on Industrial Engineering and Operations Management Kuala Lumpur, Malaysia, January 22 – 24*.

Wakiru, J., Pintelon, L., Muchiri, P., & Chemweno, P. (2019). Maintenance objective selection framework applicable to designing and improving maintenance programs. *International Journal of Engineering Research in Africa*, *43*, 127-144.

Wen, S., Buyukada, M., Evrendilek, F., & Liu, J. (2020). Uncertainty and sensitivity analyses of co-combustion/pyrolysis of textile dyeing sludge and incense sticks: Regression and machine-learning models. Renewable Energy, 151, 463-474.

Wireman, T. (2010). *Benchmarking Best Practices in Maintenance Management (2nd edition).* New York: Industrial Press Inc.

Wisniewski R. (2019). Using Weibull analysis to guide preventative maintenance strategy – DSIAC Fall 2014: Volume 1 Number 2.

Wu, Z., Guo, B., Tian, X., & Zhang, L. (2019). A dynamic condition-based maintenance model using inverse Gaussian process. IEEE Access, 8, 104-117.

Zhou, P., & Yin, P. T. (2019). An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics. Renewable and Sustainable Energy Reviews, 109, 1-9.

Zulkafli, N. I., & Mat Dan, R. (2016). Undefined. Journal of Quality in Maintenance Engineering, 22(3), 252-263. doi:10.1108/jqme-08-2015-0039

APPENDICES

Appendix 1:Interview/ Questions

How often do you encounter secondary damage complications?

☐Very Often

☐Once In A While

☐Rarely

Leave a Note:
………………………………………………………………………………………

Are secondary damages a major concern to the department?

☐YES

☐NO

Leave a Note:
………………………………………………………………………………………

Do you spend overtime performing maintenance on the machines?

☐YES

☐NO

☐SOMETIMES

Leave a Note: ………………………………………………………………………………

Are you comfortable and satisfied while operating the machines?

☐YES

☐NO

Leave a Note:
………………………………………………………………………………………

Appendix 2: Questionnaire

BM – Breakdown maintenance PM –Preventive maintenance

Your response to these questions will be highly appreciated.

1. What is the name of the department you work in?
2. What are the Types of Maintenance strategies in the department?
3. Do you have a Maintenance Policy? If any, provide it.
4. What is the approach of attending to machines?
5. What is the duration between the routine BM?
6. What Challenges do you face as a department?
7. Give the average duration needed to scan for failure?
8. Do you use the PM maintenance strategy often?
9. What is the total number of failures?
10. Number of failures that calls for BM
11. What is the average time to repair the machine?
12. What is the average time to the next machine failure?
13. Do you have a failure assessment policy?
14. What is the Average Daily machine uptime recorded?
15. What is the Average Daily machine downtime recorded?
16. List the PM Practices?
17. List the BM Practices?
18. What is the average duration needed for PM practices?
19. Number of machines on the floor
20. What is the number of machines that are not working?

21. What is the number of employees in the maintenance departments?

22. What is the duration wasted due to additional events?

23. In your opinion, which is the dominant strategy used in the department?

Appendix 3:Weibull parameters results comparison.

		X	Shape parameter	Scale parameter
Rapier weaving machine	Reed system	X1	0.962948	2672.12
	warp let-off system	X2	1.41806	1679.88
	fabric take-up system	X3	1.92714	2905.03
	machine main drive system	X4	2.07718	2470.29
	selvedge formation system	X5	107.874	2195.58
	connectivity system	X6	5.10607	5404.90
Air-jet weaving machines	weft feeders system	X7	8.36824	1420.21
	reed system	X8	7.42371	5344.08
	warp let-off system	X9	2418.89	1000.75
	fabric take-up system	X10	24.6176	547754
	machine drive system	X11	2.94138	14728.8
	harness frames system	X12	1.88017	2139.04
	selvedge formation system	X13	0.987828	1151.01
	connectivity system	X14	1.84369	15294.9
	lubrication fabric take-up, and let-off system	X15	222.157	1231.69
	Total time operation time	X16	14.8479	24873.2
	lubrication main drive	X17	1.88327	5673.38
	Number of failures	X18	3.03961	4.26714
	MTBF	Y	1.46503	1683.46

Appendix 4: Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
404.541	85.56%	85.30%	84.91%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-17267	24130	-0.72	0.474	
X1 Age of the system	0.00712	0.00449	1.58	0.114	1.02
X2 Age of the system	0.0104	0.0126	0.83	0.409	1.02
X3 Age of the system	0.01112	0.00897	1.24	0.215	1.02
X4 Age of the system	-0.0206	0.0122	-1.69	0.092	1.02
X5 Age of the system	-1.001	0.502	-1.99	0.046	1.02
X6 Age of the system	-0.0124	0.0117	-1.06	0.290	1.01
X7 Age of the system	-0.0288	0.0688	-0.42	0.676	1.01
X8 Age of the system	-0.0298	0.0159	-1.87	0.062	1.01
X9 Age of the system	20.3	23.9	0.85	0.396	1.01
X10 Age of the system	0.0548	0.0484	1.13	0.258	1.02
X11 Age of the system	-0.00259	0.00281	-0.92	0.356	1.01
X12 Age of the system	-0.0144	0.0110	-1.31	0.192	1.02
X13 Age of the system	0.0105	0.0112	0.94	0.348	1.01
X14 Age of the system	-0.00161	0.00174	-0.93	0.354	1.02
X15 Age of the system	0.51	1.86	0.27	0.784	1.03
X16 Age of the system	0.00154	0.00676	0.23	0.820	1.04
X17 Age of the system	0.30017	0.00485	61.94	0.000	1.02

X18 Number of Events/Failures -398.04 9.91 -40.16 0.000 1.02

Regression Equation

Y Response = MTBF = -17267 + 0.00712 X1 Age of the system + 0.0104 X2 Age of the system

+ 0.01112 X3 Age of the system - 0.0206 X4 Age of the system

- 1.001 X5 Age of the system - 0.0124 X6 Age of the system

- 0.0288 X7 Age of the system - 0.0298 X8 Age of the system

+ 20.3 X9 Age of the system + 0.0548 X10 Age of the system

- 0.00259 X11 Age of the system - 0.0144 X12 Age of the system

+ 0.0105 X13 Age of the system - 0.00161 X14 Age of the system

+ 0.51 X15 Age of the system + 0.00154 X16 Age of the system

+ 0.30017 X17 Age of the system - 398.04 X18 Number of Events/Failures

Appendix 5: The appendix presents Weibull distribution analysis for the various system components in the loom.

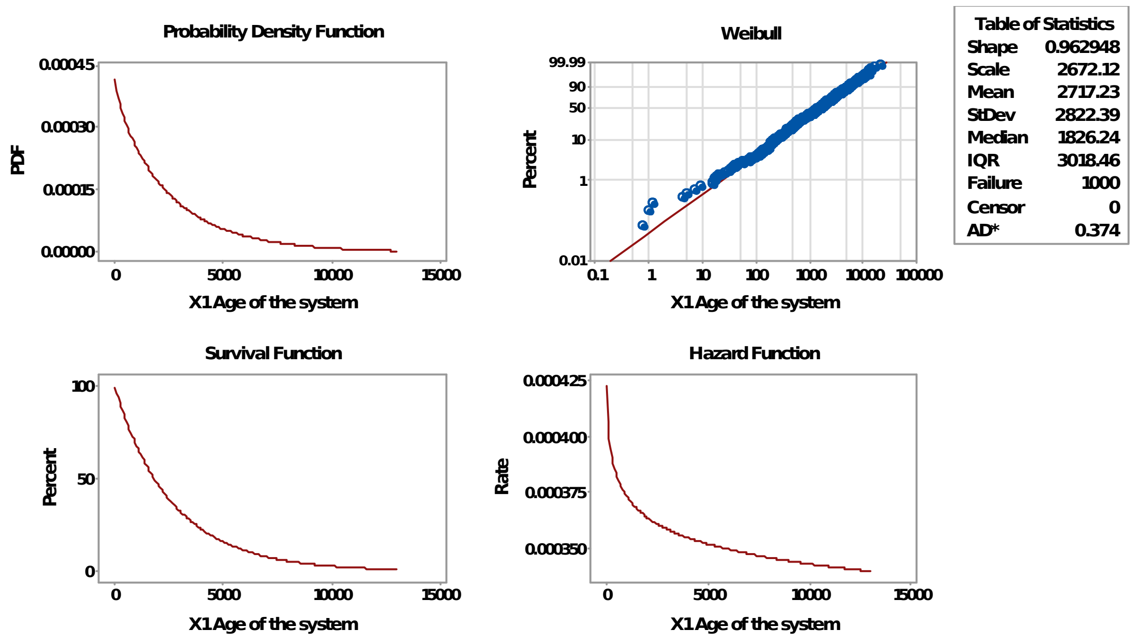


Figure 3: Distribution and probability Plot for Reed System in Rapier Weaving Machine.

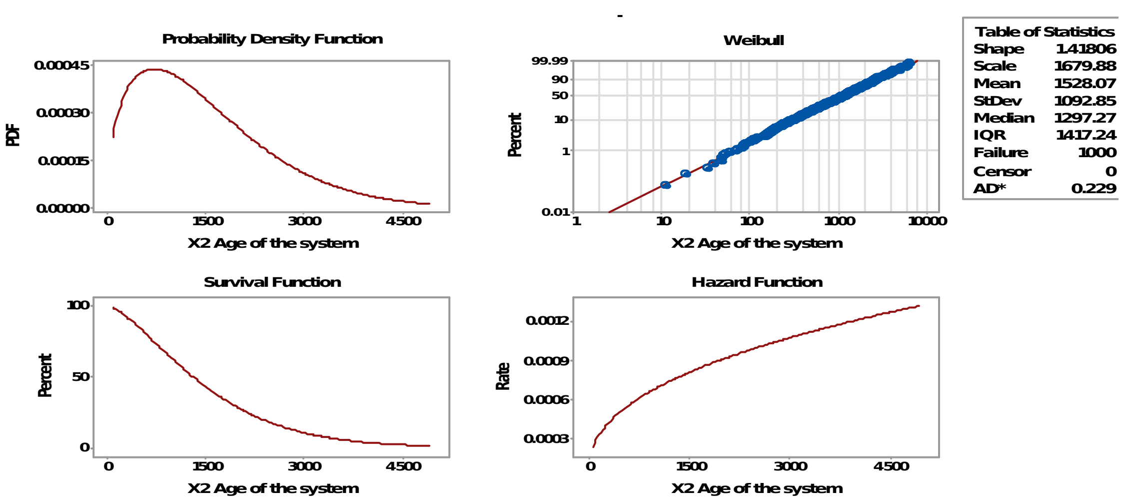


Figure 2: Distribution and probability Plot for Warp Let-Off System in Rapier Weaving Machine.

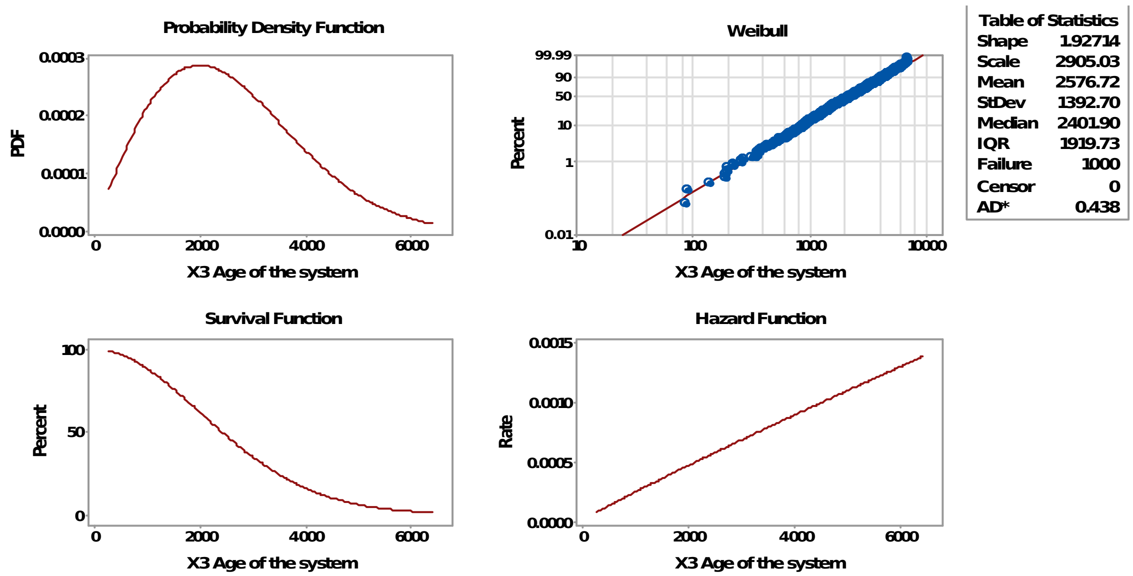


Figure 3: Distribution and probability Plot for Fabric Take-Up System in Rapier Weaving Machine.

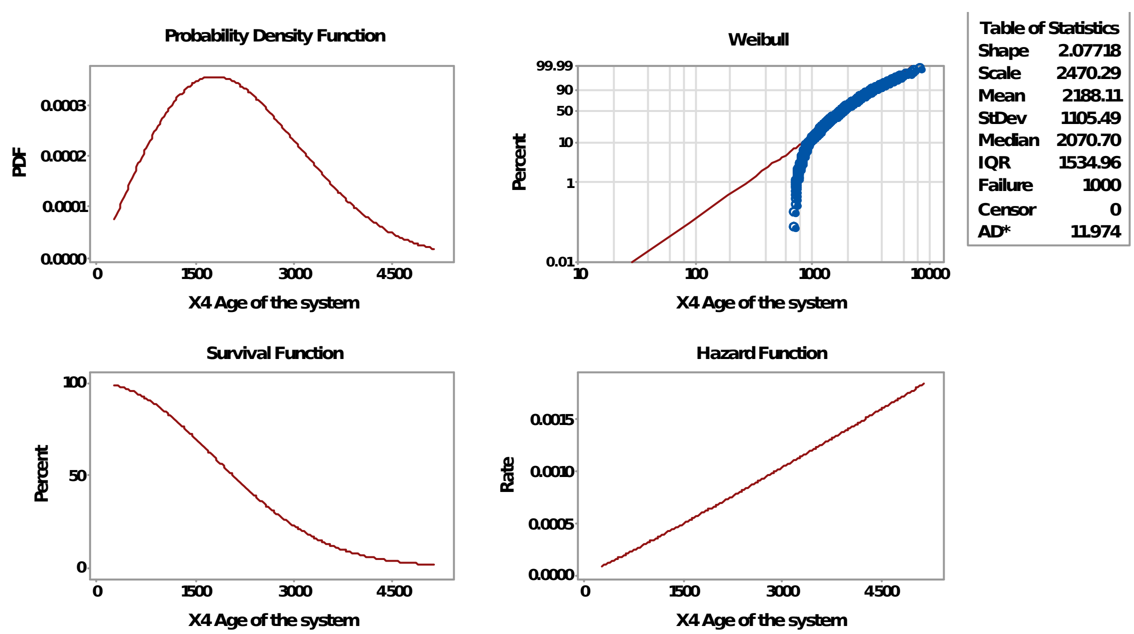


Figure 4: Distribution and probability Plot for Machine Main Drive System in Rapier Weaving Machine.

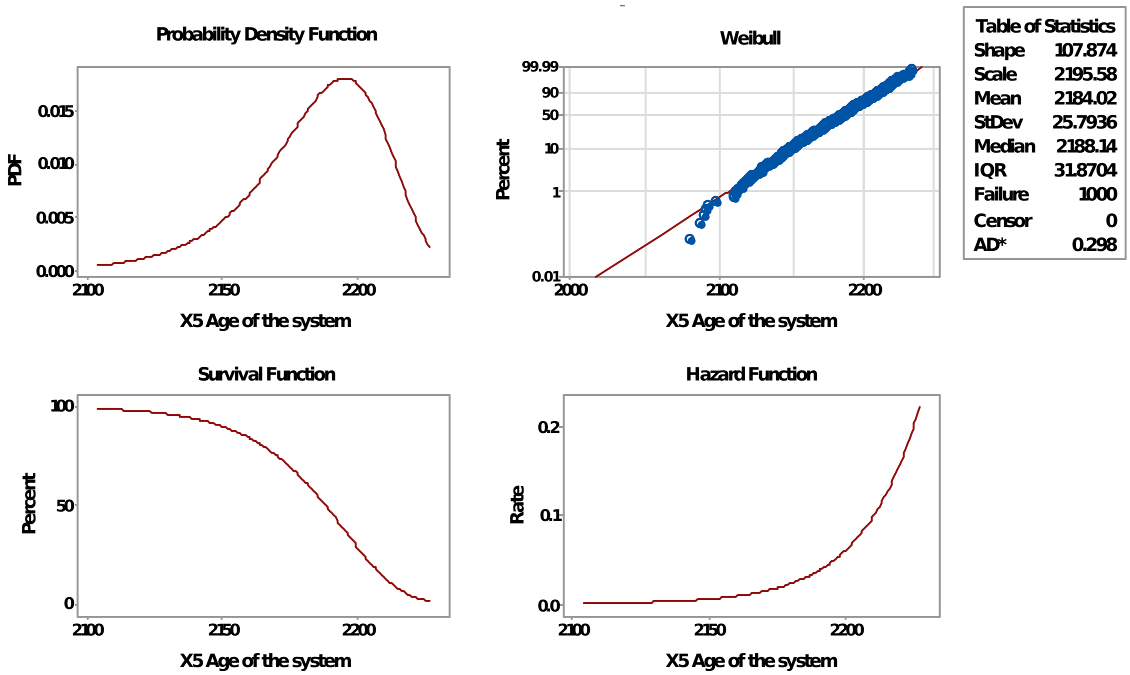


Figure 5: Distribution and probability Plot for Selvedge Formation System in Rapier Weaving Machine.

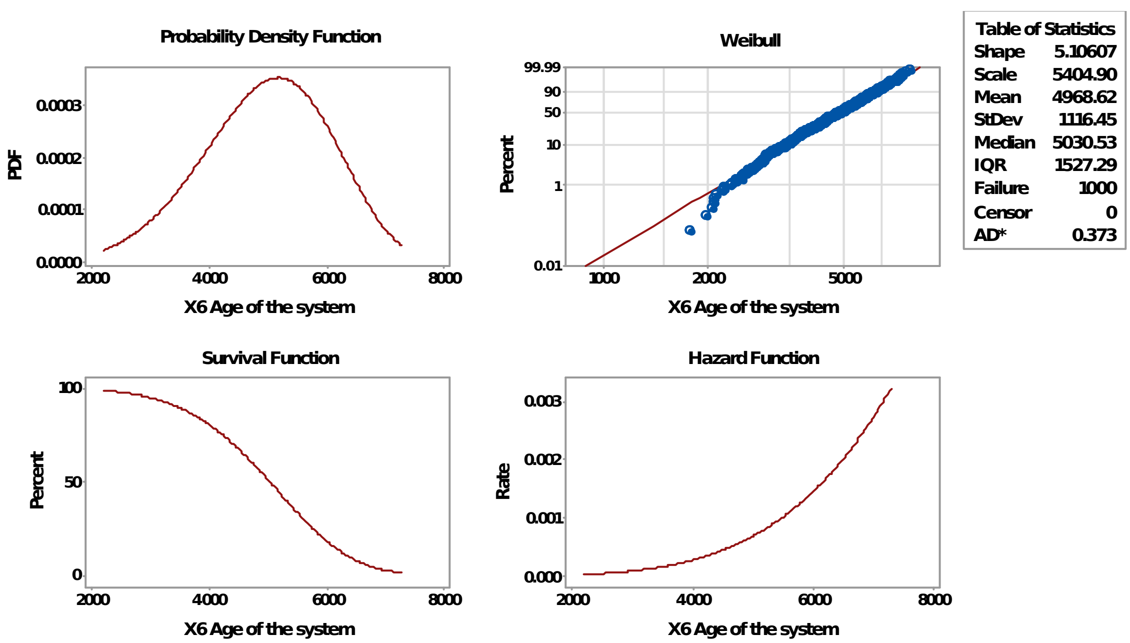


Figure 6: Distribution and probability Plot for Connectivity System in Rapier Weaving Machine.

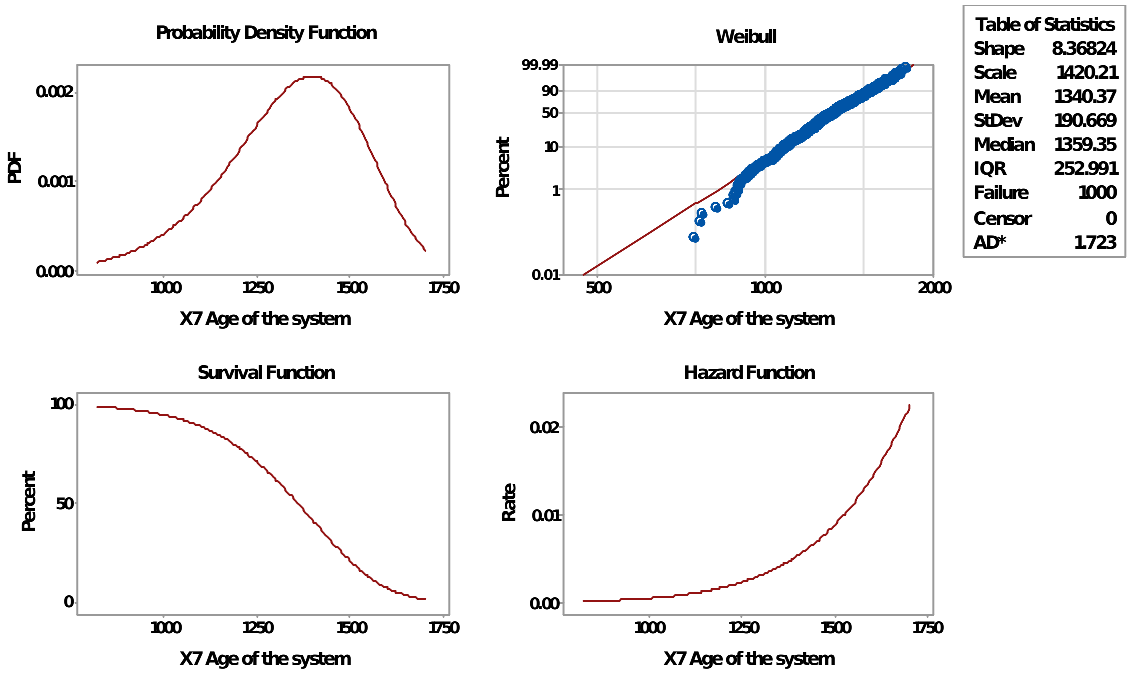


Figure 7: Distribution and probability Plot for Weft Feeders System in Airjet Weaving Machine.

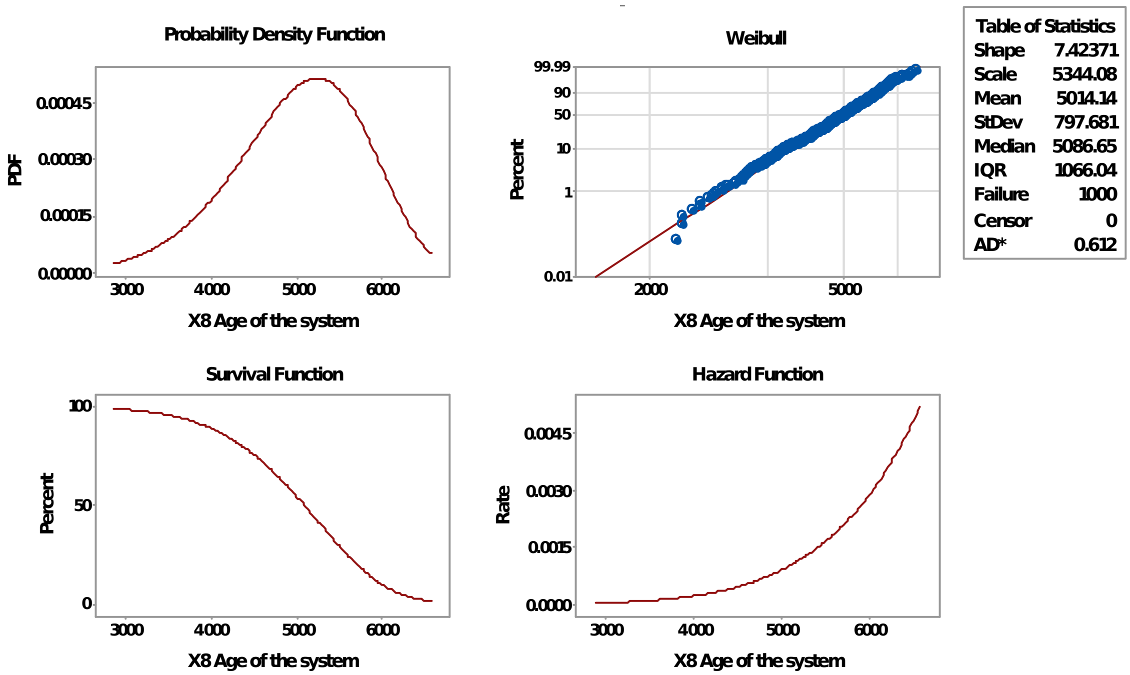


Figure 8: Distribution and probability Plot for Reed System in Airjet Weaving Machine.

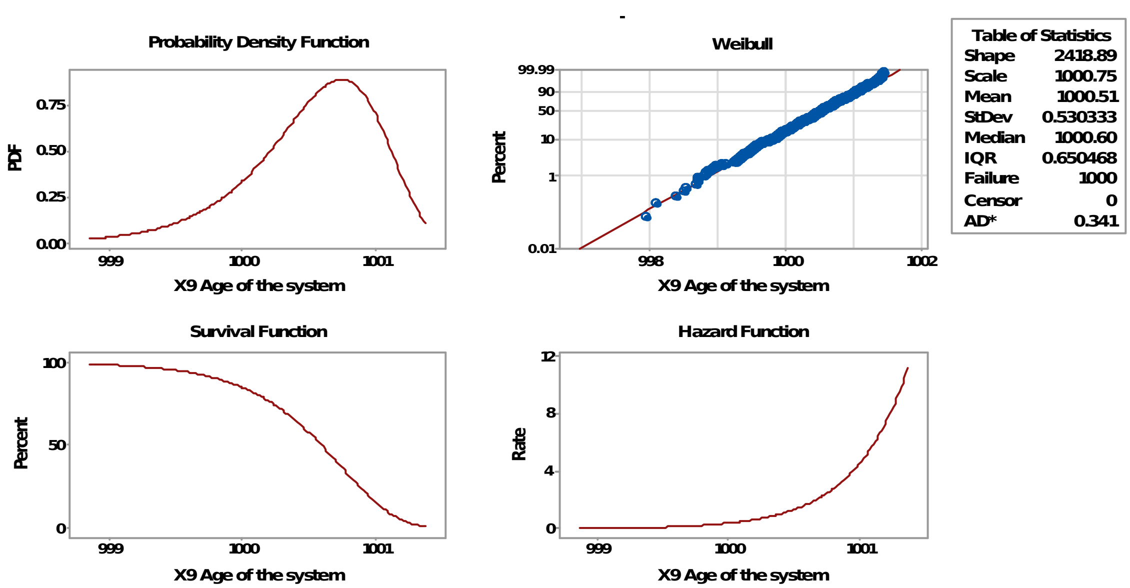


Figure 9: Distribution and probability Plot for Warp Let-Off System in Airjet Weaving Machine.

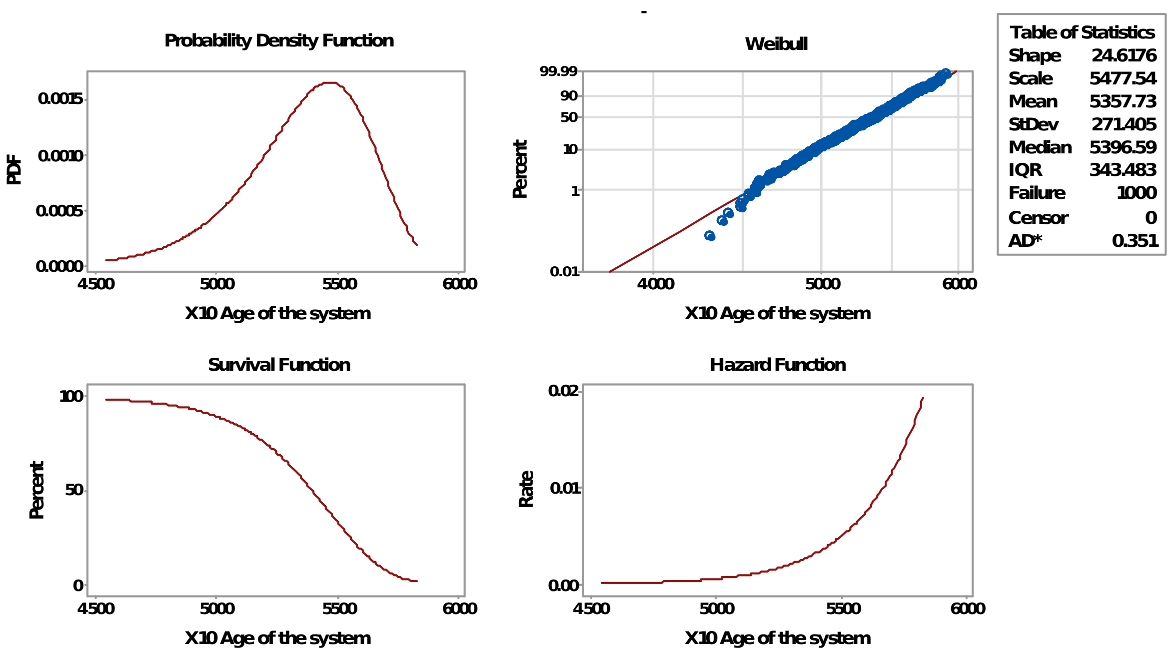


Figure 10: Distribution and probability Plot for Fabric Take-Up System in Airjet Weaving Machine.

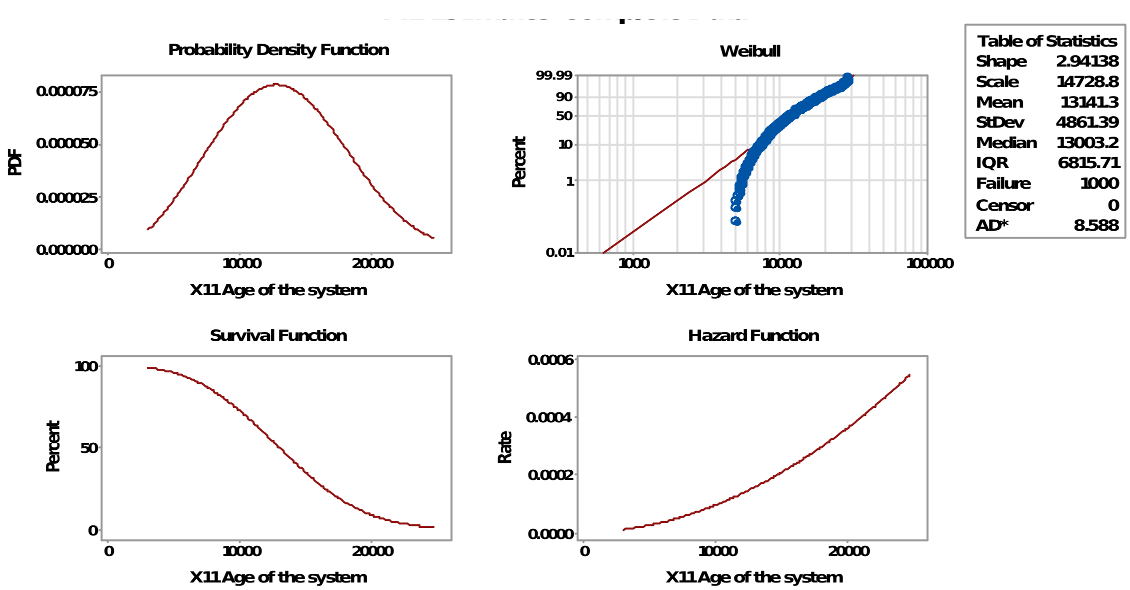


Figure 411: Distribution and probability Plot for Machine Drive System in Airjet Weaving Machine.

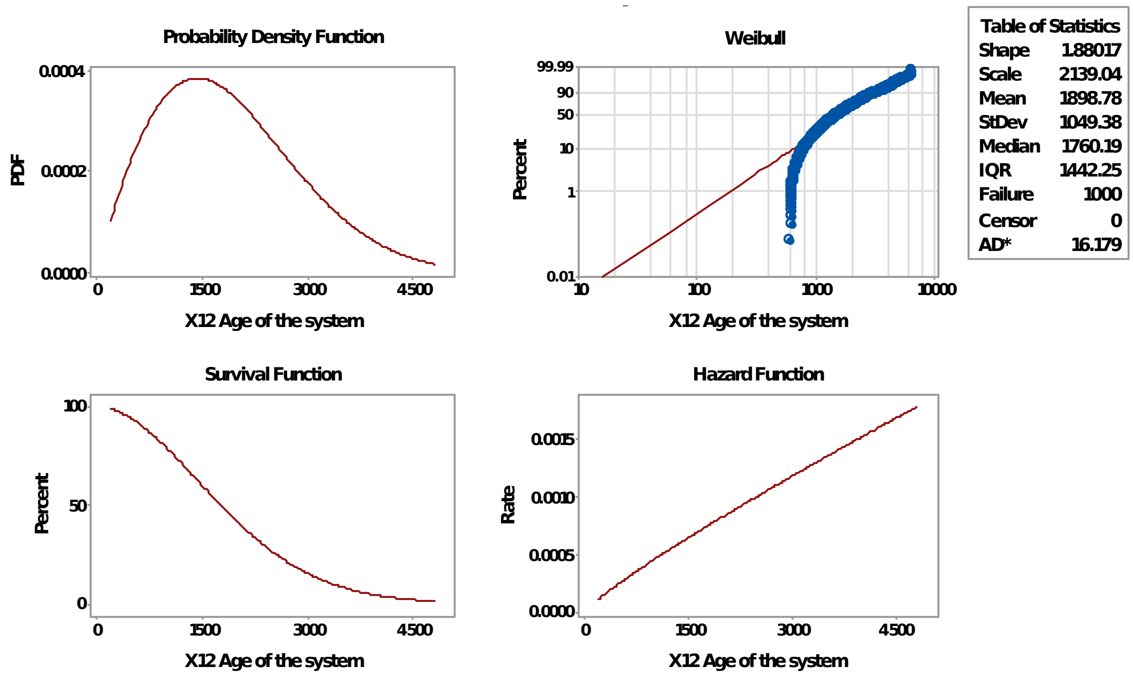


Figure 12: Distribution and probability Plot for Harness Frames System in Airjet Weaving Machine.

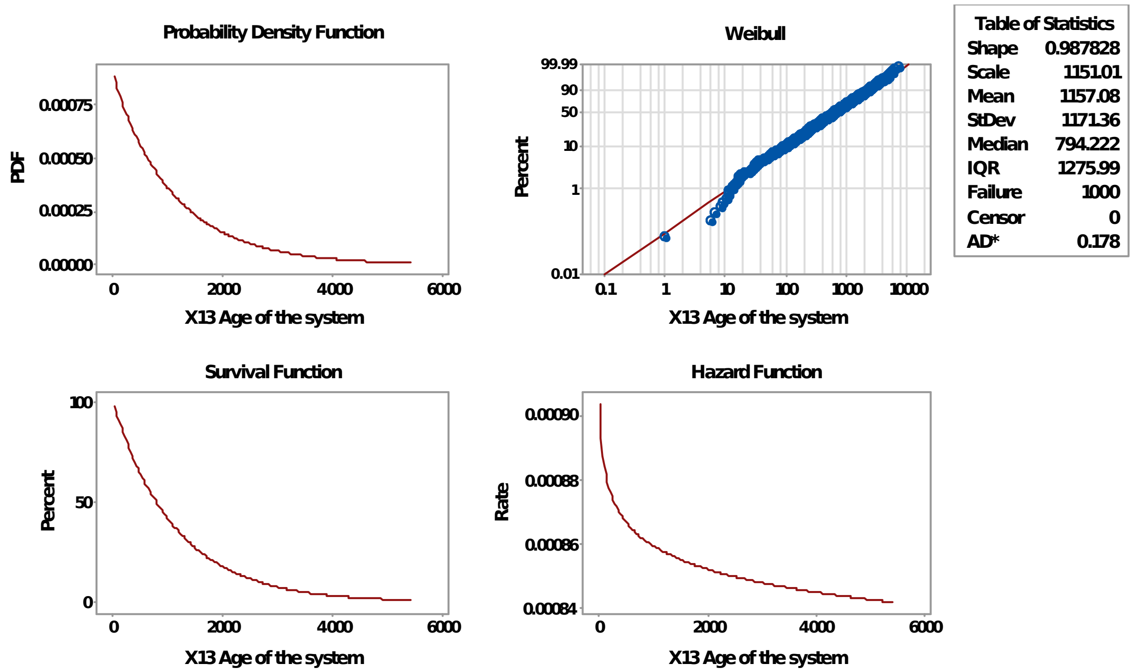


Figure 13: Distribution and probability Plot for Selvedge Formation System in Airjet Weaving Machine.

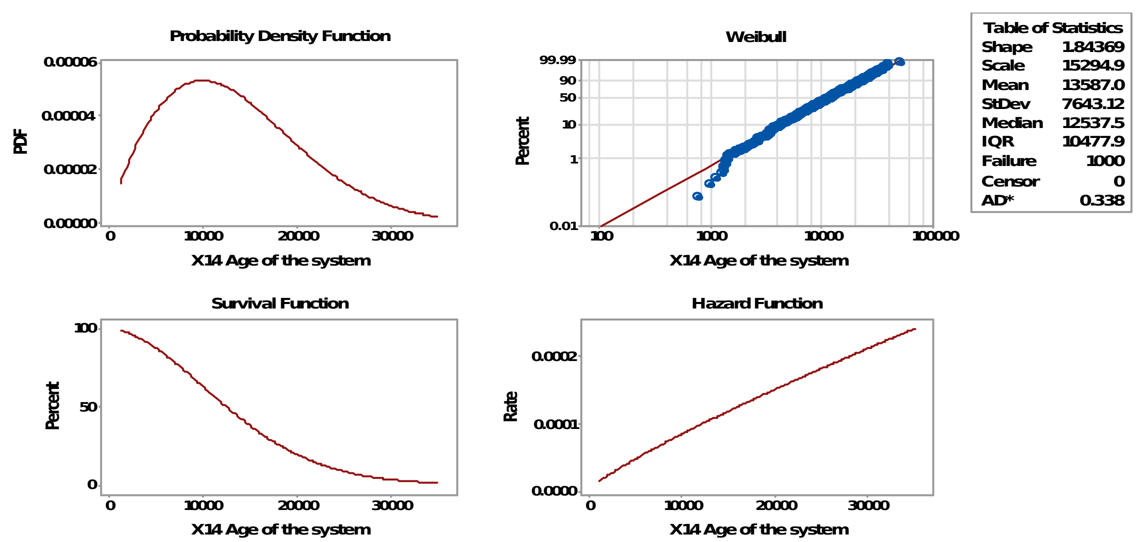


Figure 14: Distribution and probability Plot for Connectivity System in Airjet Weaving Machine.

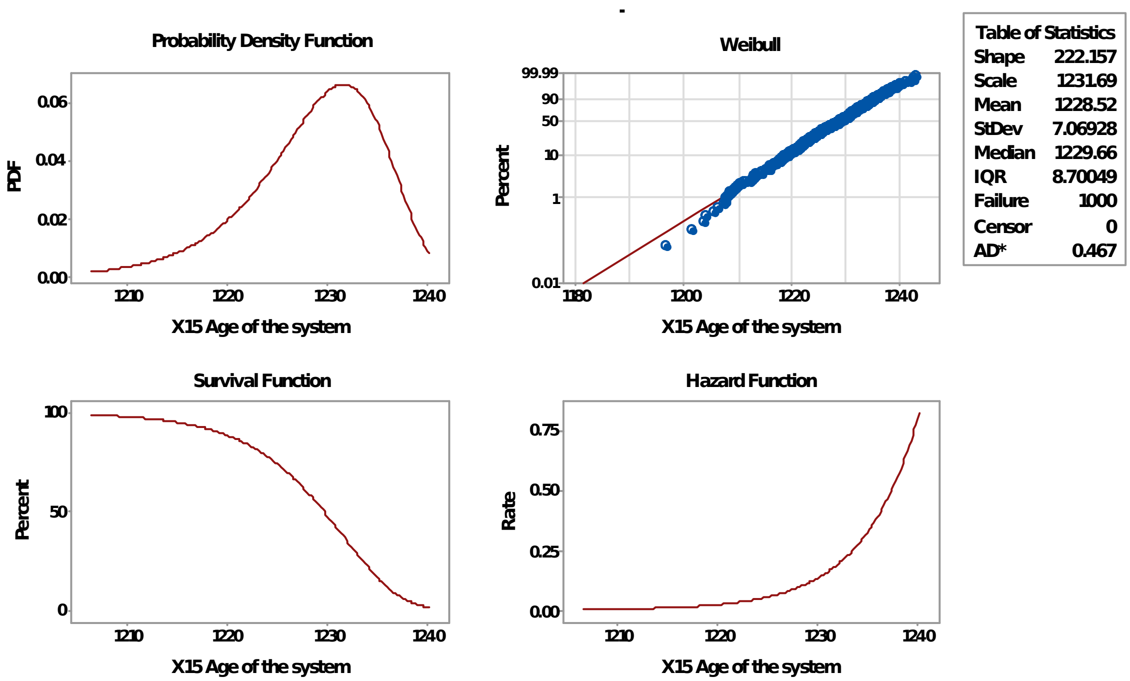


Figure 15: Distribution and probability Plot for Lubrication Fabric Take-Up and Let off in both Rapier and Airjet Weaving Machines.

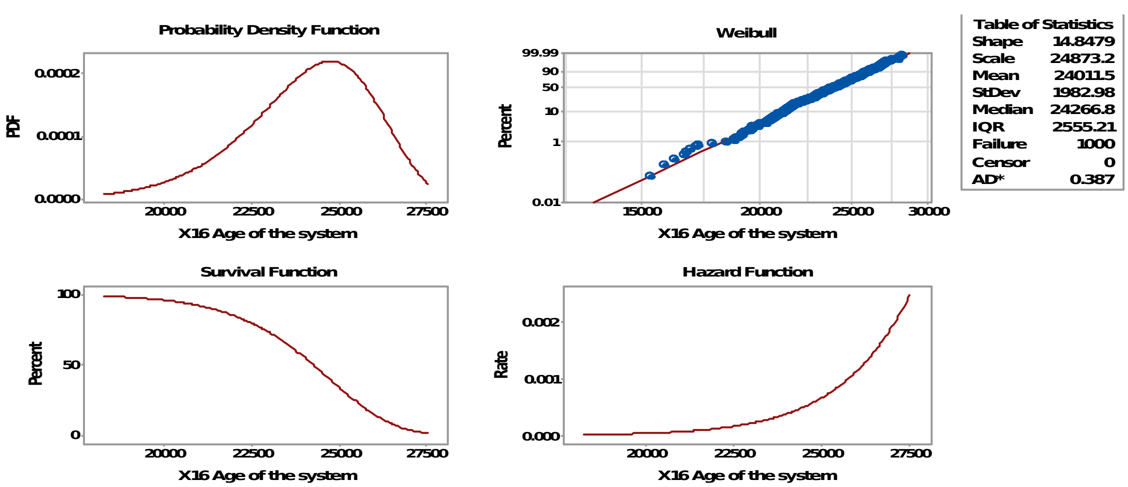


Figure 16: Distribution and probability Plot for Lubrication of main drive in both Rapier and Airjet Weaving Machines.

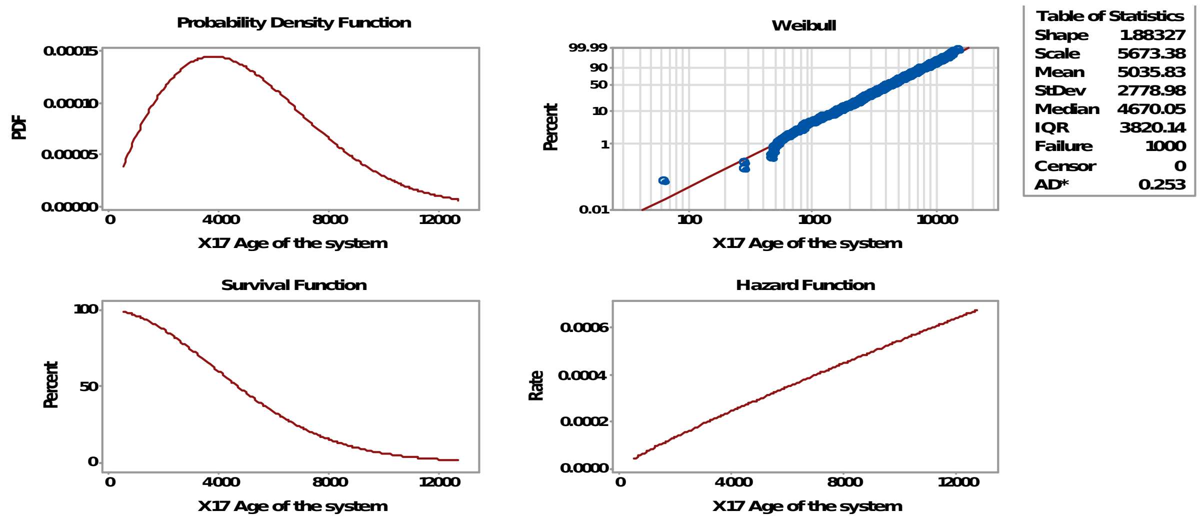


Figure 17: Distribution and probability Plot for Total Time for both Rapier and Airjet Weaving Machines.

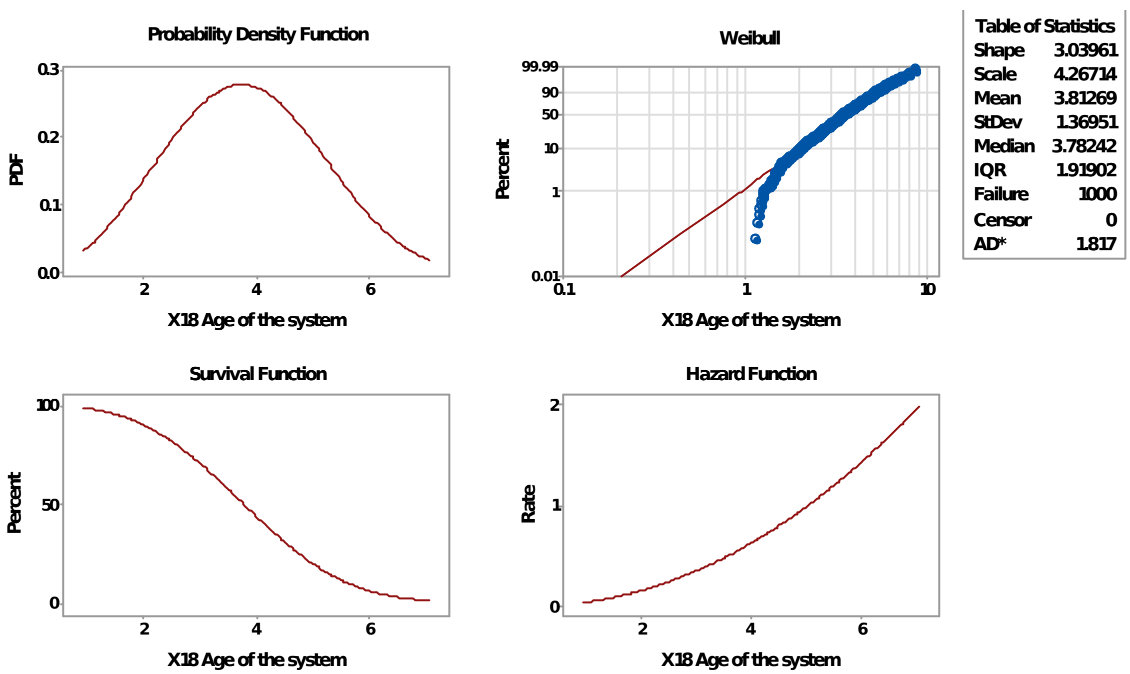


Figure 18: Distribution and probability Plot for number of failures for both Rapier and Airjet Weaving Machines.

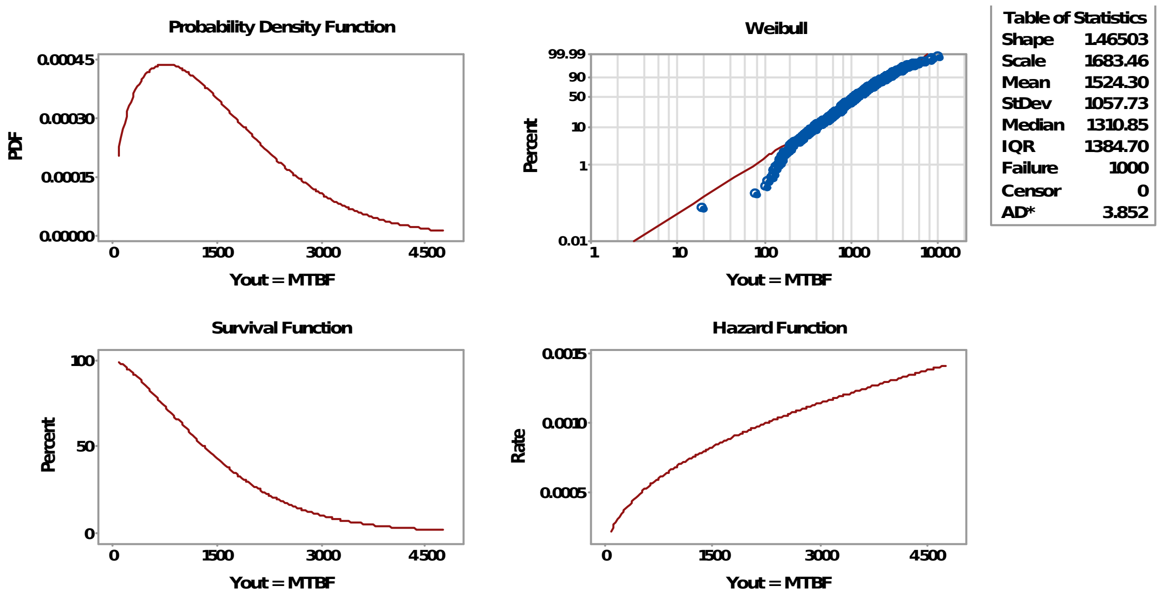


Figure 19: Distribution and probability Plot for Response, MTBF.

Appendix 6

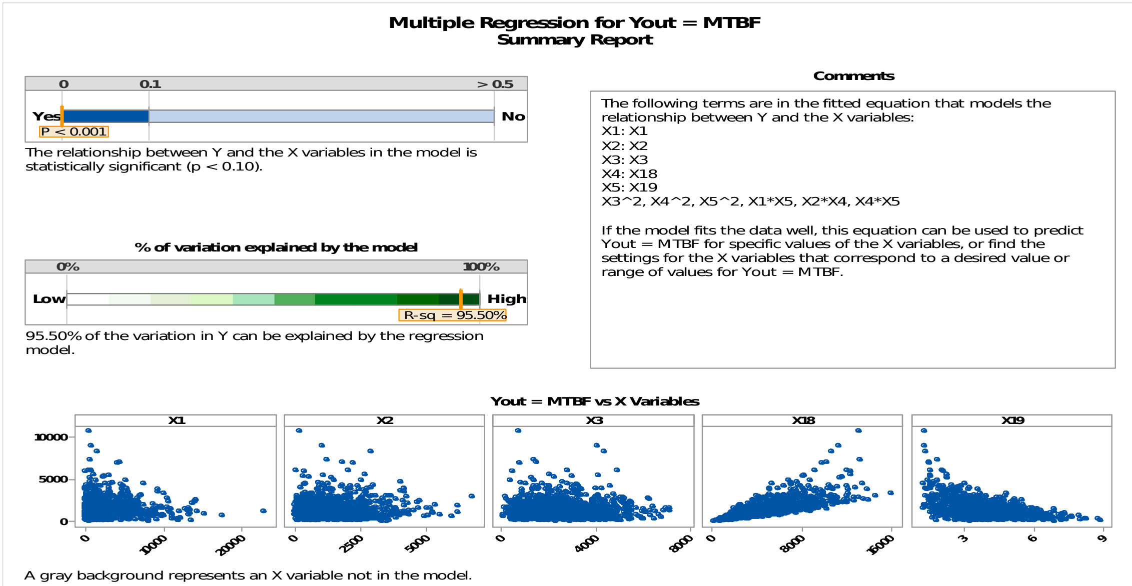
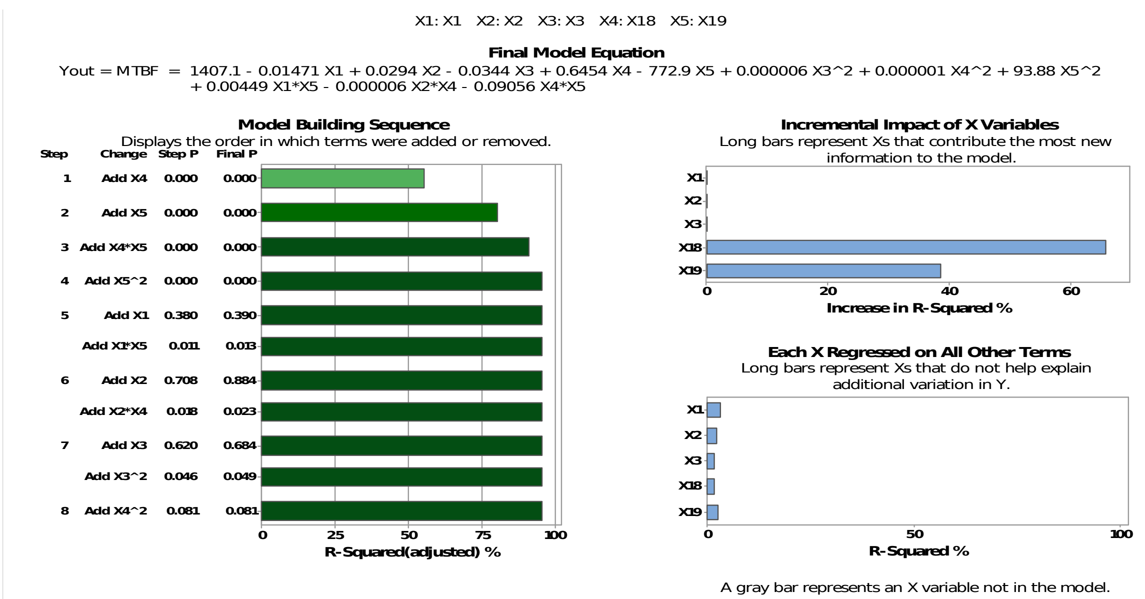


Figure 1: Variation in MTBF due to reed system, warp let-off system, and fabric take-up system in rapier machines and total time and number of failures.



Step	Change	Step P	Final P
1	Add X4	0.000	0.000
2	Add X5	0.000	0.000
3	Add X4*X5	0.000	0.000
4	Add X5^2	0.000	0.000
5	Add X1	0.380	0.390
	Add X1*X5	0.011	0.013
6	Add X2	0.708	0.884
	Add X2*X4	0.018	0.023
7	Add X3	0.620	0.684
	Add X3^2	0.046	0.049
8	Add X4^2	0.081	0.081

Figure 2: Modeling report for MTBF, reed system, warp let-off system, and fabric take-up system in rapier machines and total time and number of failures.

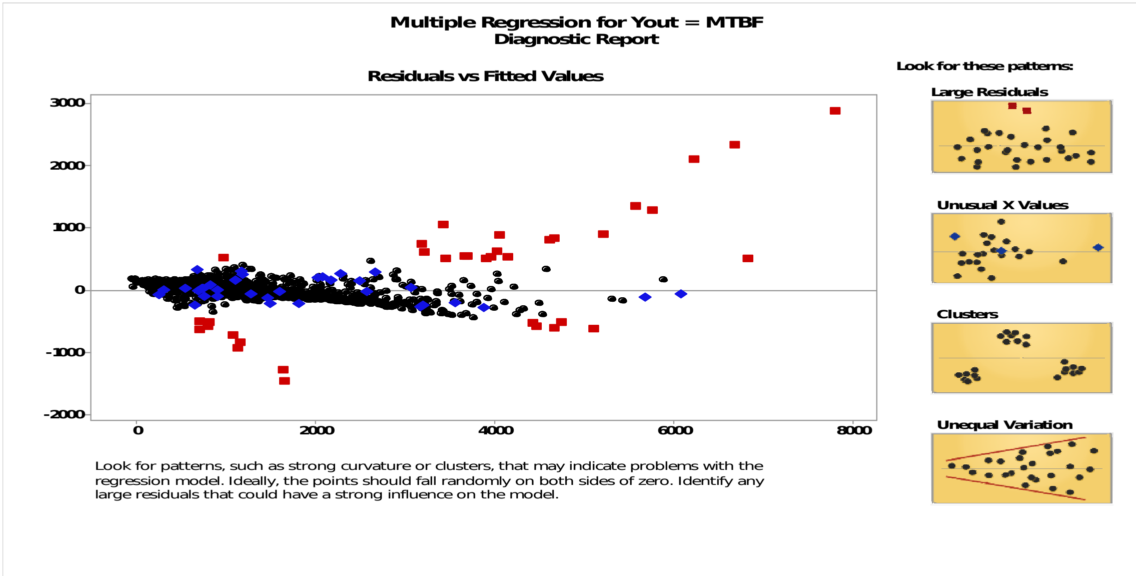


Figure 3: Fitting values of reed system, warp let-off system, and fabric take-up system in rapier machines and total time and number of failures.

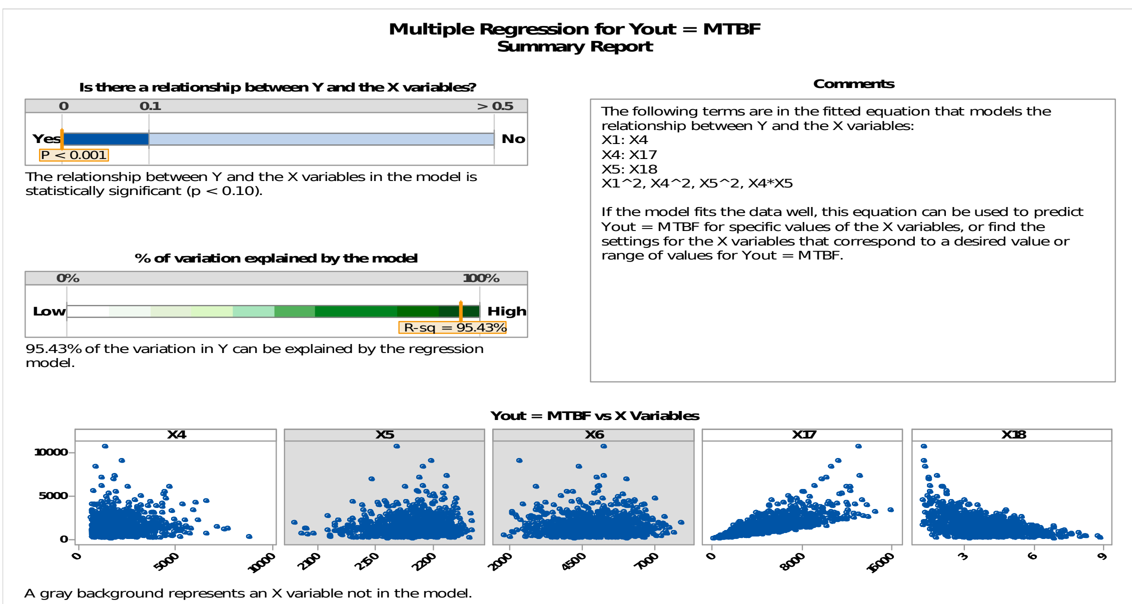


Figure 4: Variation in MTBF due to machine main drive system, selvedge formation system, and connectivity system in rapier machines and the total time and number of failures.

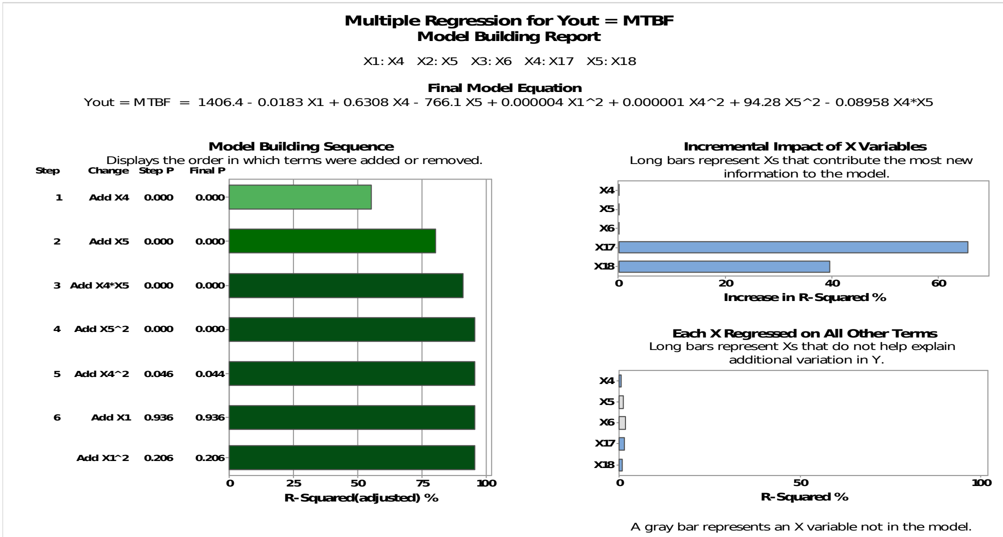


Figure 5: Modeling report for MTBF, machine main drive system, selvedge formation system, and connectivity system in rapier machines and the total time and number of failures.

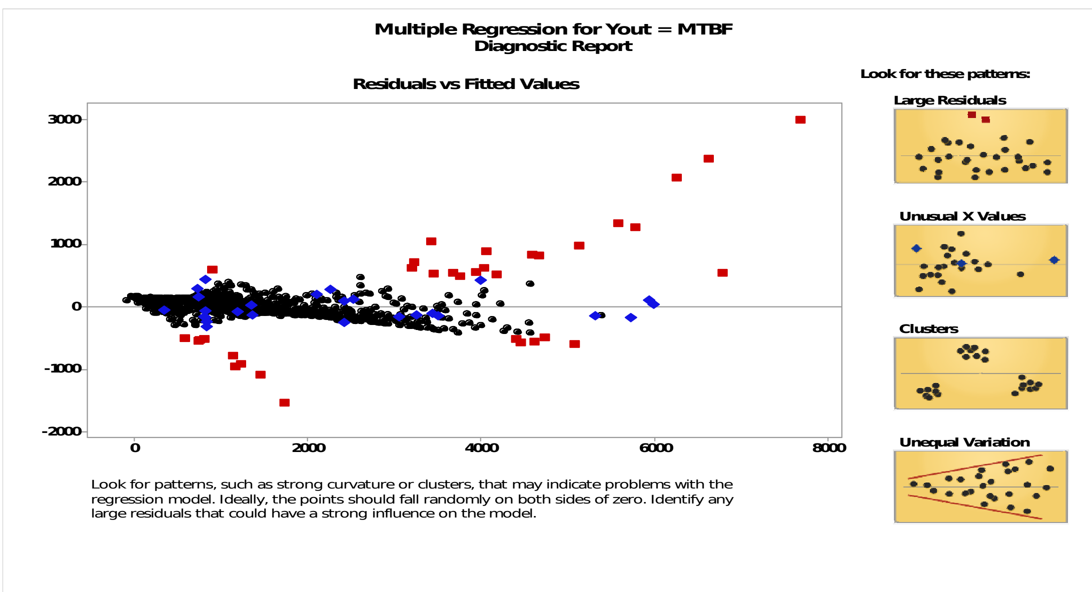


Figure 6: Fitting values of machine main drive system, selvedge formation system, and connectivity system in rapier machines and the total time and number of failures.

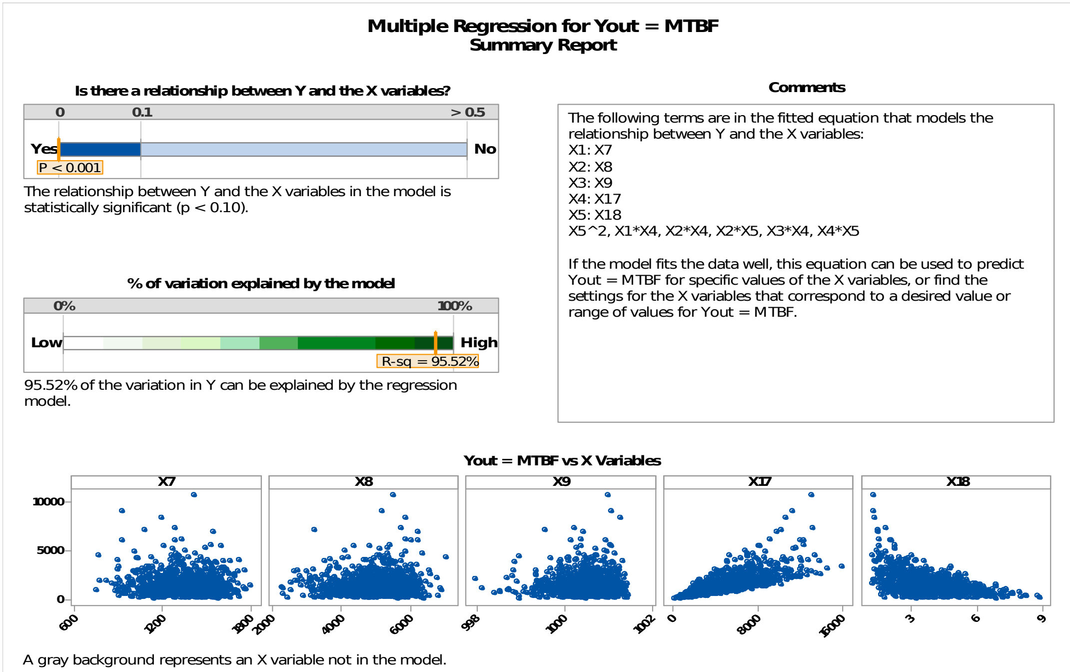


Figure 7: Variation in MTBF due to weft feeder system, reed system, and warp let-off system in air-jet machine and total time and number of failures.

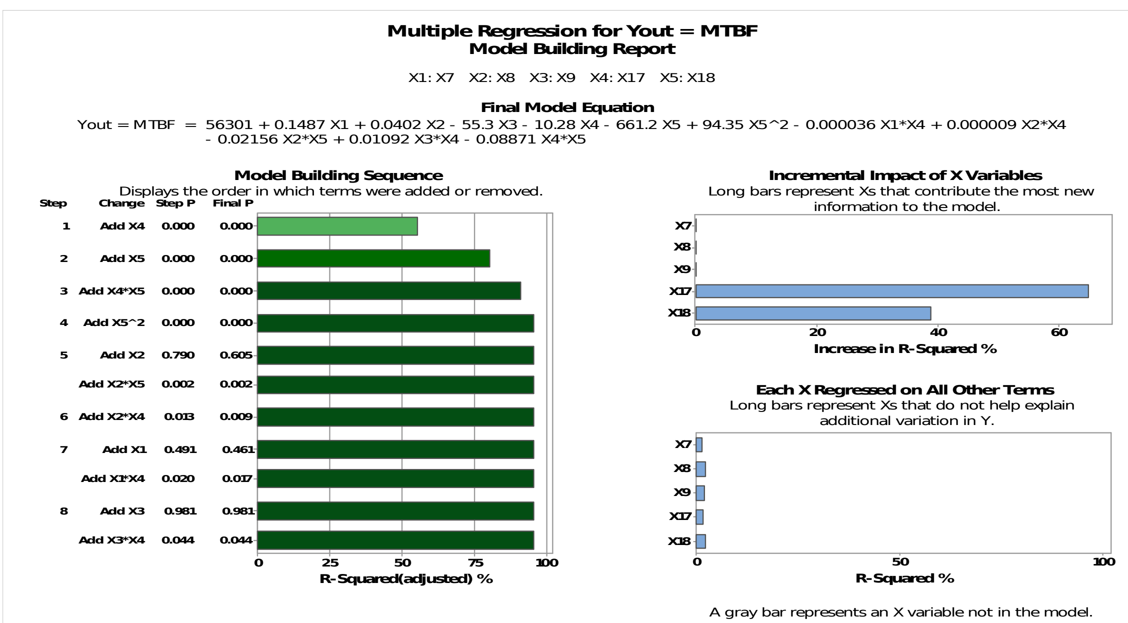


Figure 8: Modeling report for MTBF, weft feeder system, reed system, and warp let-off system in air-jet machine and total time and number of failures.

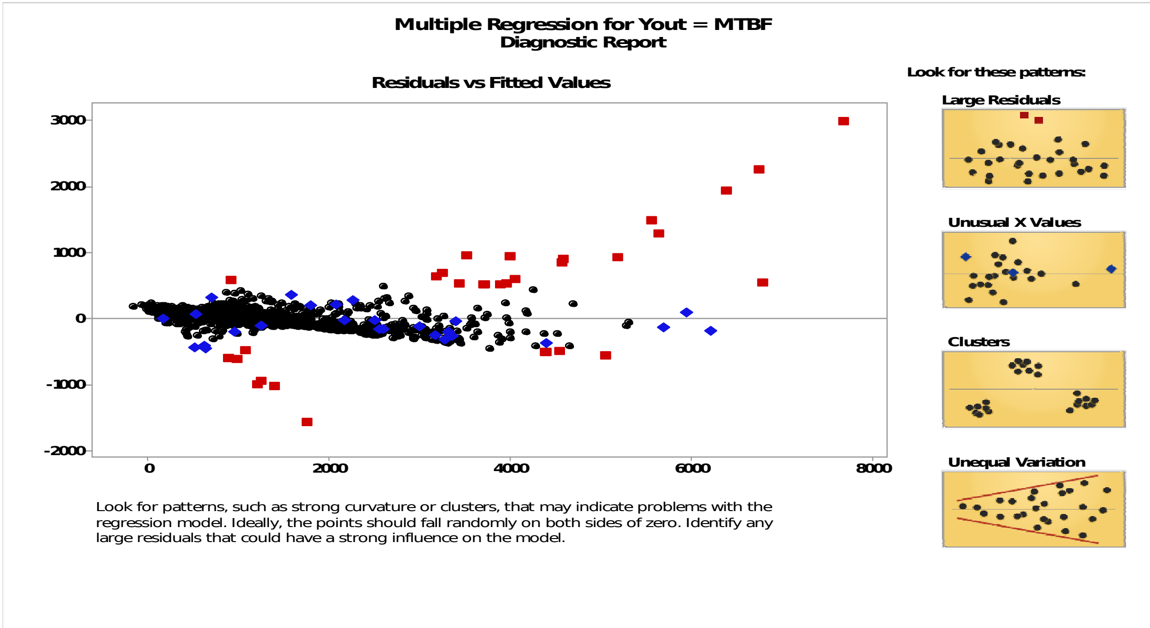


Figure 9: Fitting values of weft feeder system, reed system, and warp let-off system in air-jet machine and total time and number of failures.

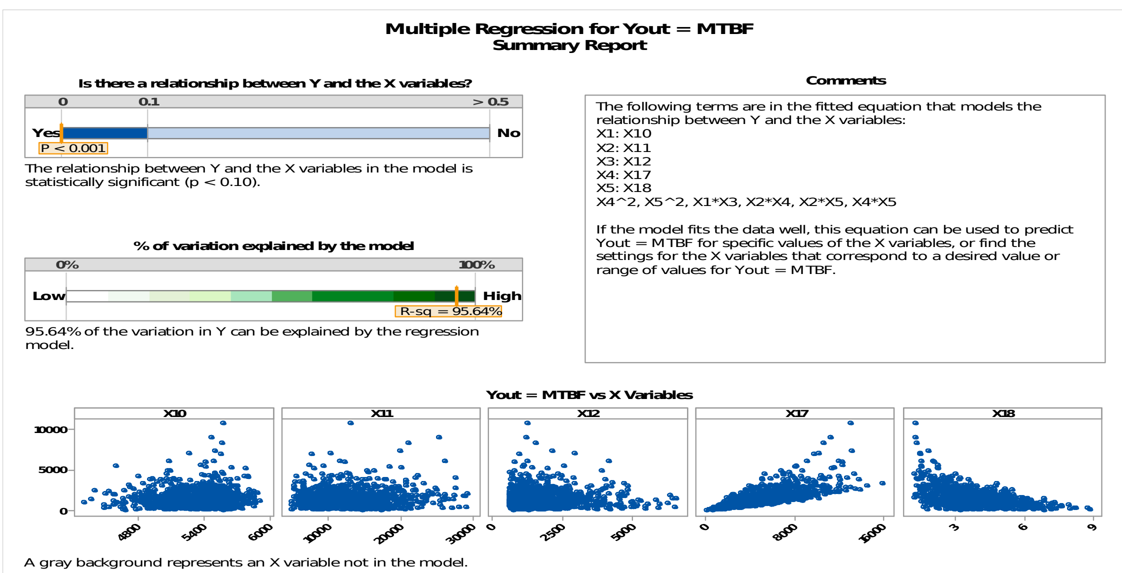


Figure 10: Variation in MTBF due to fabric take-up system, machine drive system, and harness frames system in air-jet machines and total time and number of failures.

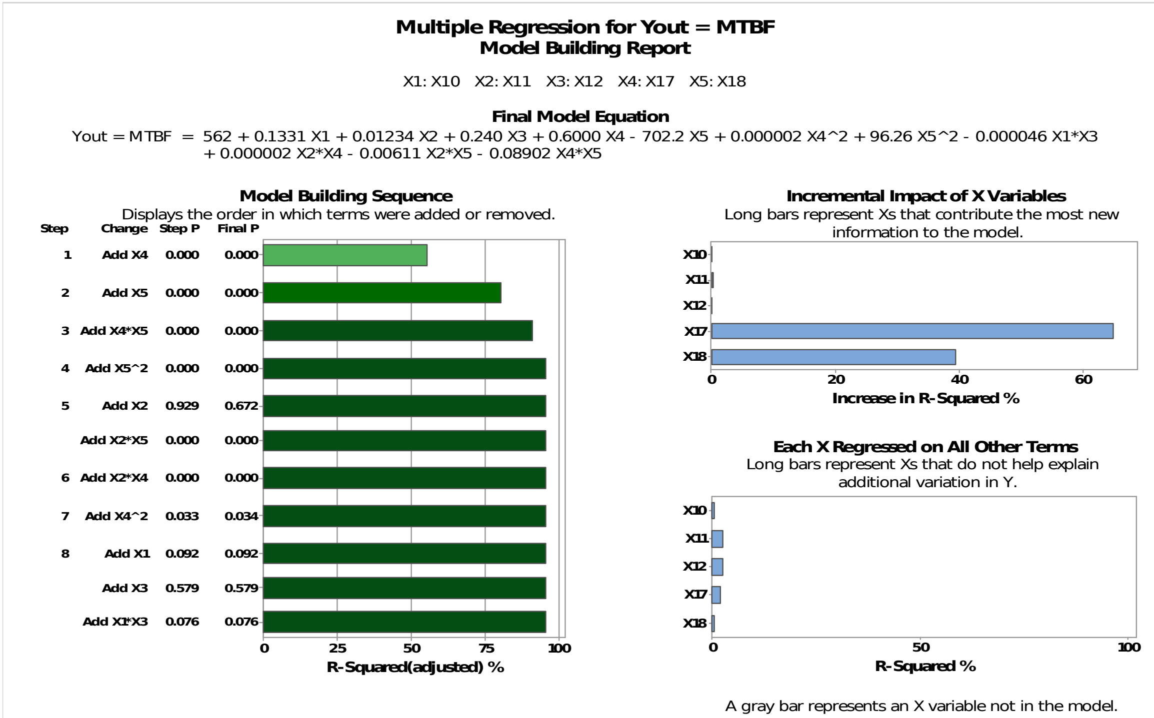


Figure 11: Modeling report for MTBF, fabric take-up system, machine drive system, and harness frames system in air-jet machines and total time and number of failures.

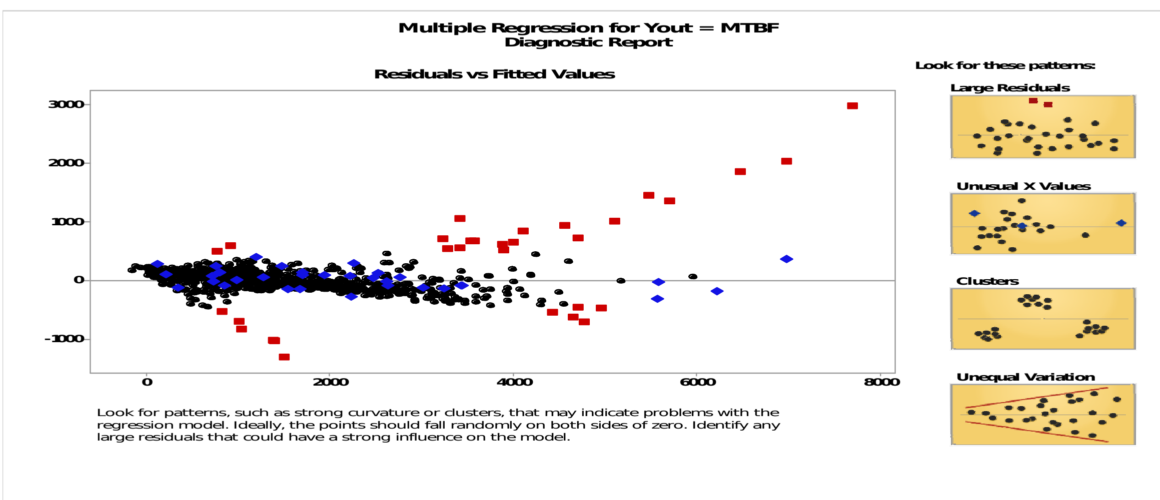


Figure 12: Fitting values of fabric take-up system, machine drive system, and harness frames system in air-jet machines and total time and number of failures.

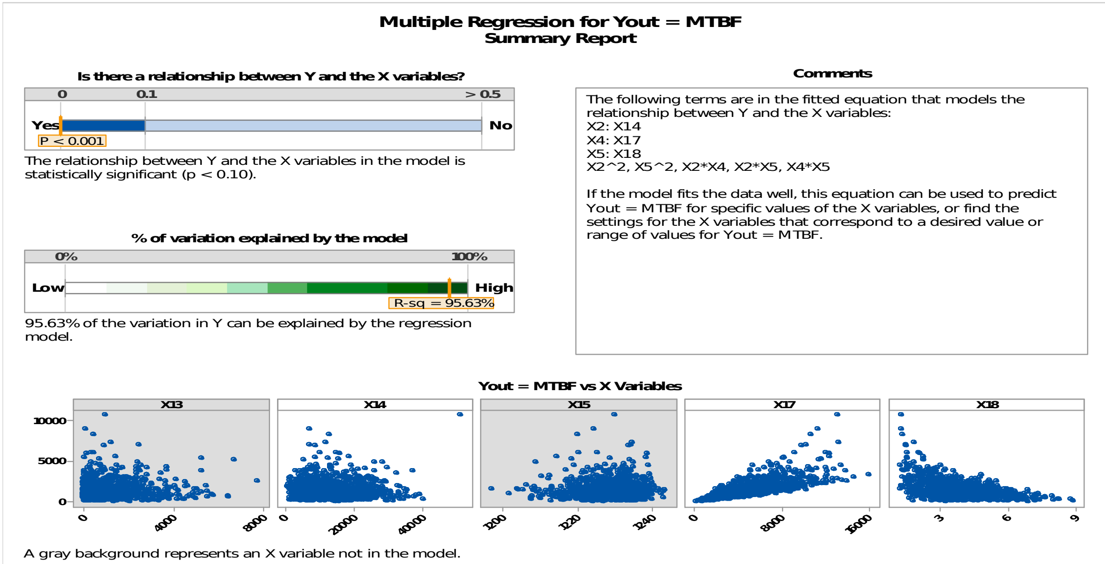


Figure 13: Variation in MTBF due to selvedge formation system and connectivity system in the air-jet machine as well as lubrication fabric take-up and let off total time, and number of failures.

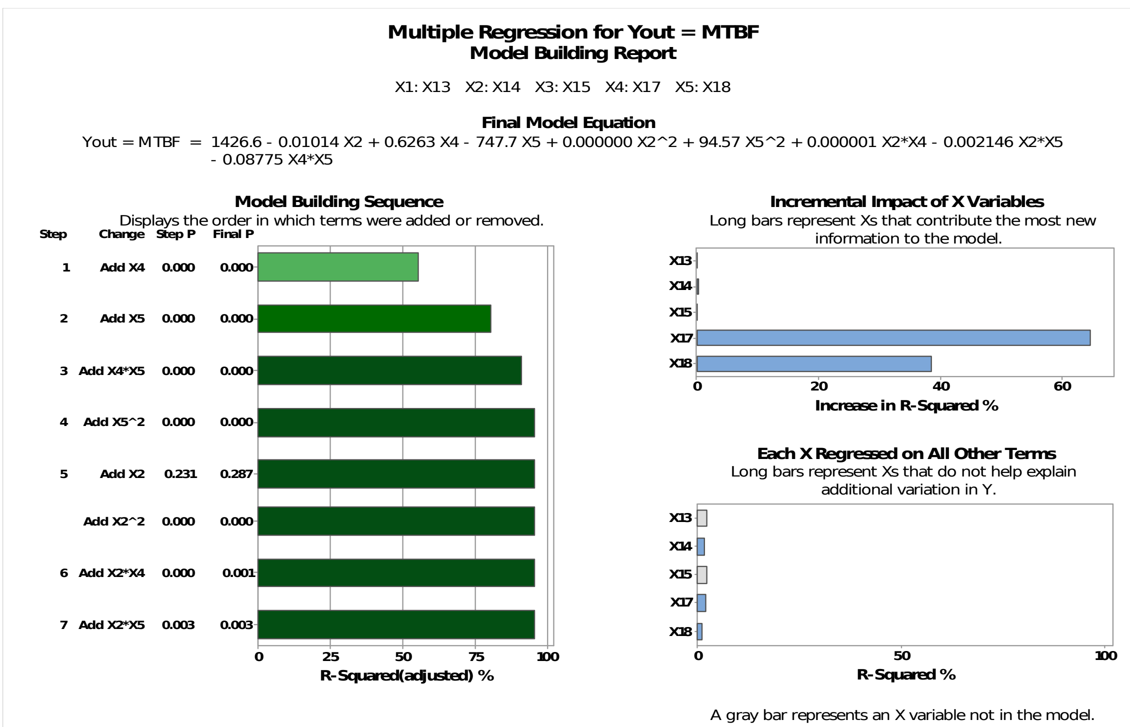


Figure 14: Modeling report for MTBF, selvedge formation system and connectivity system in the air-jet machine as well as lubrication fabric take-up and let off, total time and number of failures.

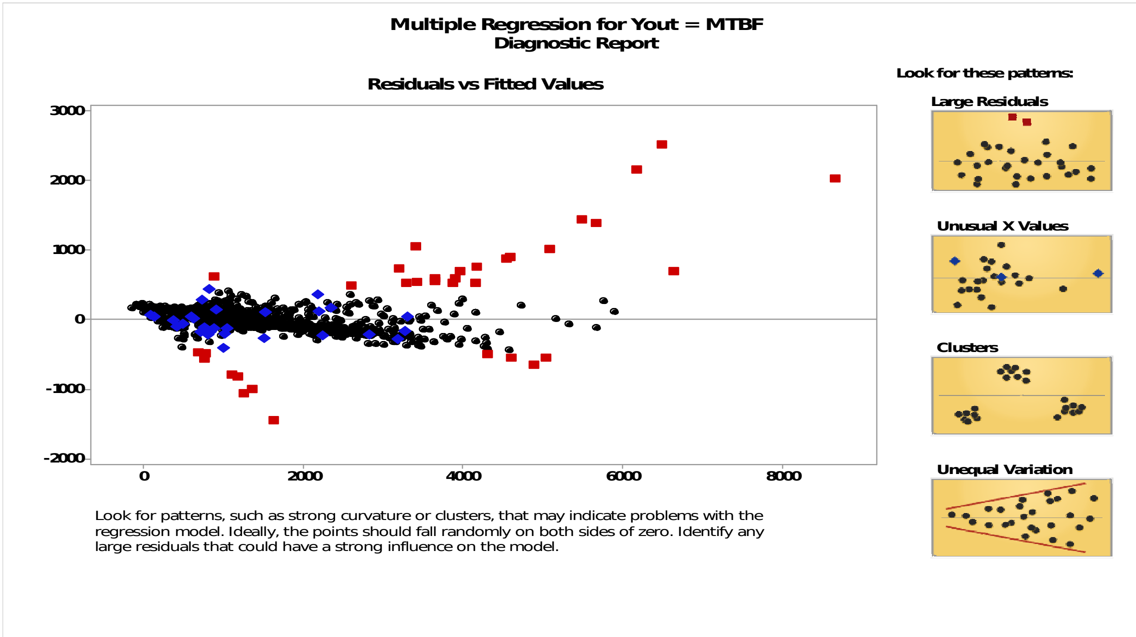


Figure 15: Fitting values of selvedge formation system and connectivity system in the air-jet machine as well as lubrication fabric take-up and let off, total time and number of failures.

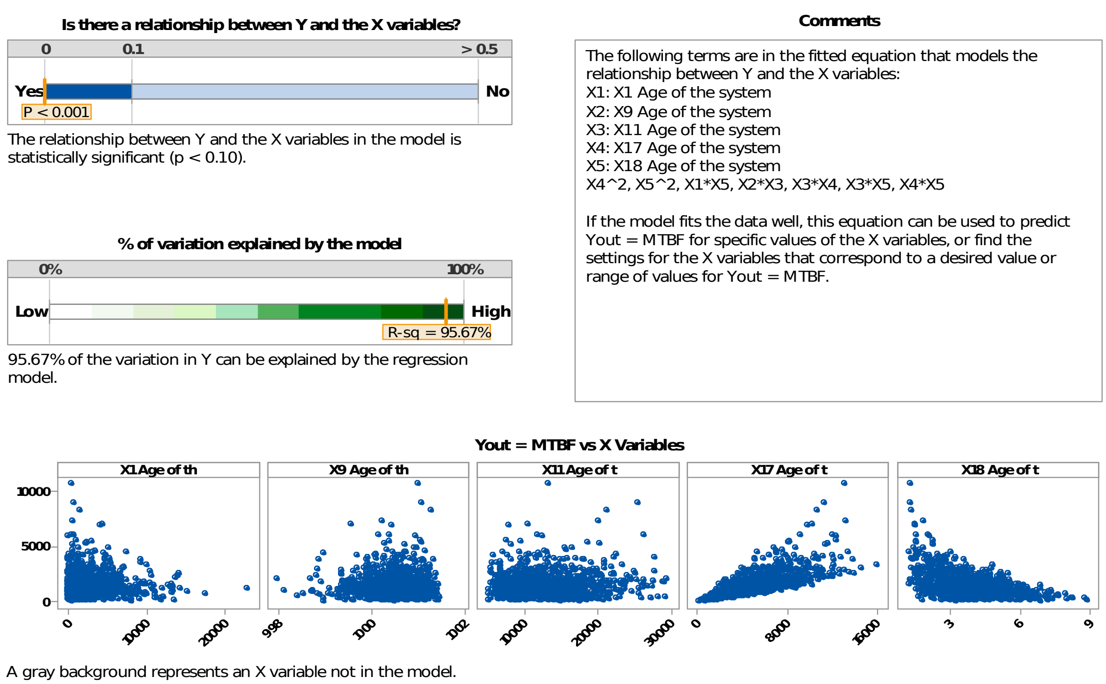


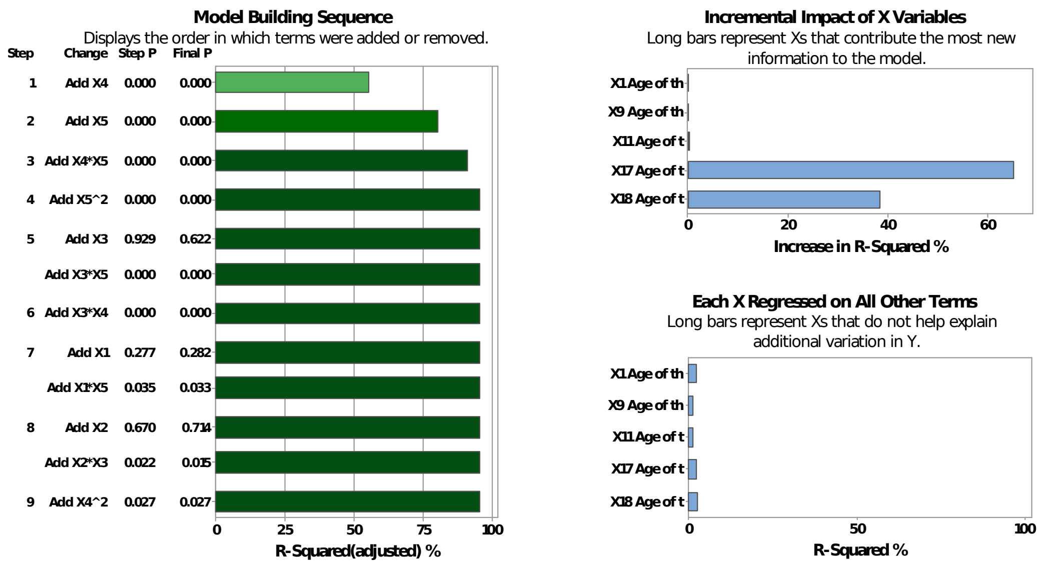
Figure 16: Variation in MTBF due to reed system (rapier), machine drive system (air-jet), warp let-off system (air-jet), total time, and number of failures.

Multiple Regression for Yout = MTBF
Model Building Report

X1: X1 Age of th X2: X9 Age of th X3: X11 Age of t X4: X17 Age of t X5: X18 Age of t

Final Model Equation

$$Yout = MTBF = 93095 - 0.01149\, X1 - 91.8\, X2 - 7.38\, X3 + 0.6015\, X4 - 700.3\, X5 + 0.000002\, X4^2 + 94.56\, X5^2 + 0.00379\, X1{*}X5 + 0.00738\, X2{*}X3 + 0.000002\, X3{*}X4 - 0.00569\, X3{*}X5 - 0.09001\, X4{*}X5$$



A gray bar represents an X variable not in the model.

Figure 17: Modeling report for MTBF, reed system (rapier), machine drive system (air-jet), warp let-off system (air-jet), total time and number of failures.

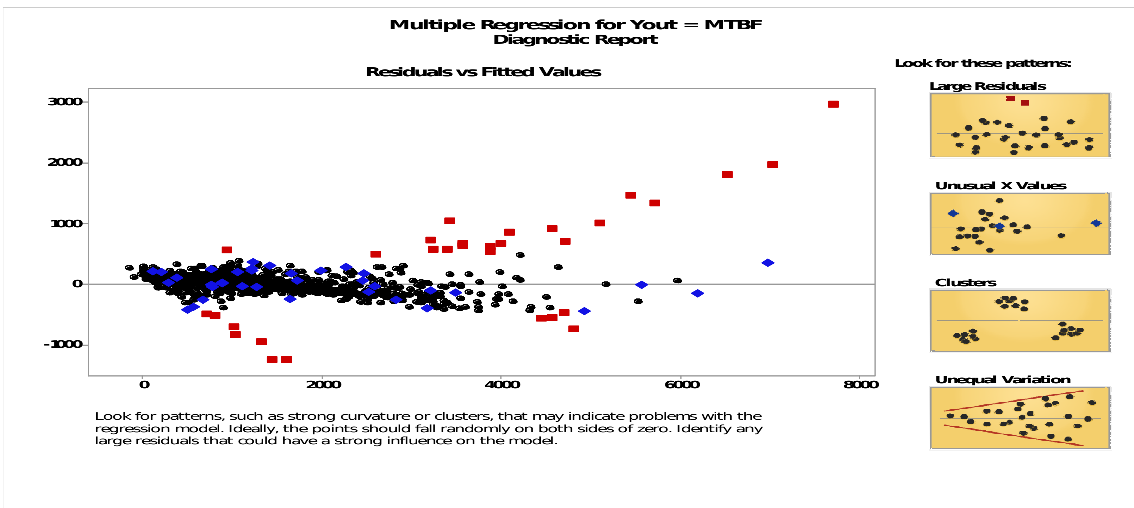


Figure 18: Fitting values of reed system (rapier), machine drive system (air-jet), warp let-off system (air-jet), total time, and number of failures.