OPTIMIZATION OF MAINTENANCE PERFORMANCE MEASUREMENT OF CRITICAL MACHINES IN TEA PROCESSING: A CASE STUDY AT LITEIN TEA FACTORY

BY

LANGAT JACKSON BIRIR

A Thesis Submitted to the School of Engineering, Department of Manufacturing Industrial and Textile Engineering, in Partial Fulfilment of the Requirements for the Award of Degree of Master of Science in Industrial Engineering

Moi University

2024

DECLARATION

Declaration by the Candidate

This thesis is my original work and has not been presented in any other University for the award of a master's degree. No part of this thesis may be reproduced without prior permission of the author and /or Moi University.

Signature ………………….… Date……………………

Langat Jackson Birir

TEC/PGMT/04/15

Declaration by Supervisors

This research project has been submitted for examination with my approval as Moi University supervisor.

Signature ………………….… Date……………………

Dr. Jerry Ochola

Department of Manufacturing, Industrial and Textile Engineering, School of Engineering

Moi University

Signature ………………….… Date……………………

Dr. Peter Chemweno

Department of Design, Production & Management, University of Twente, The Netherlands

Signature ………………….… Date……………………

Dr. Eric Oyondi

Department of Manufacturing, Industrial and Textile Engineering, School of Engineering

Moi University

DEDICATION

Dedicated to my children, Matilda Chelangat, Cecilia Chepchumba and Xavier Kipkalya.

ACKNOWLEDGEMENTS

I thank the almighty God for giving me strength and good health during my studies that culminated in this thesis. Special thanks go to my supervisors, Dr. Jerry Ochola, Dr. Peter Chemweno, and Dr. Eric Oyondi for their wise counsel and mentorship as I conceived and wrote my research work. I also appreciate my classmates for the shared inspiration to refine my thesis and the motivation to finish my master's studies. I am grateful to the study respondents, including the management, administration, and maintenance staff of Litein Tea Processing Factory, within Kericho County, for giving me the opportunity to undertake this research in the company and for providing the data I needed to address my research questions. Finally, I thank my family members for their moral and spiritual support as I undertook my studies.

ABSTRACT

In industrial processing, functional and efficient plant equipment is crucial for optimum output. Therefore, proper maintenance of plant equipment can help minimize operational expenditures arising from breakdowns. The challenge has been to establish the correlation of maintenance and manufacturing performance, and the overall operational performances in product quality, product cost and plant availability. Therefore, the main objective of this study was to optimize maintenance performance measurements of critical machines in tea processing, with a case study of Litein Tea Factory, Kenya. Its specific objectives were to: identify a critical equipment in tea processing plant; evaluate a maintenance model for a critical equipment in tea processing plant and optimize the maintenance model of a critical equipment in tea industry. To identify the critical equipment, data were collected using questionnaires and analysed using Statistical Package for the Social Sciences software to evaluate criticality. From the failure mode effects analysis, Crush, Tear and Curl, with an Index of 242, was established as the most critical unit in tea processing. Data on downtime, throughput, operating time, number of failures, failure type and service time were then collected from the Crush, Tear and Curl in Excel sheet and transferred to Minitab worksheet. Probability plot for the parameters in a sample size of 28 was of normal distribution and with P-values of 0.005. Mean and Standard deviations were also tested. Correlations between the dependent (Y) (throughput and number of failures) and independent (X) variables generated a R^2 values of 89.06% for throughput and 51.72% for number of failures models. The evaluated models were validated by use of sensitivity analysis to assess how changes in input parameters affect the model output, simulated and the summary statistics derived from Monte Carlo Simulation. Initial process performances were 0.0501 for number of failures and -0.0291 for throughput regressions. Meanwhile, percentages out of specifications corresponded to highs of 59.64% for number of failures and 83.06 for throughput models. Parameter optimization was then undertaken to generate best fit and optimal variables. The results indicated process performance of 2.98 with corresponding 0.00% out of specs for the number of failure regression and 1.17 process performance and respective 0.05% out of specs performance for throughput regression model. In conclusion, utilizing optimized parameters can enable factories to improve on machine availability, reliability, maintainability, and overall efficiency. Future research should sample from many tea factories to help validate the study results. Future research should also endeavour to raise the value of R^2 in the regression for number of failures to bring the statistical figures close to the fit line.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

AHP	Analytic Hierarchy Process
BBN	Bayesian Belief Net
BSI	British Standard Institutions
CBPM	Condition Based Predictive Maintenance
CFU	Continuous Fermentation Unit
CMMS	Computerized Maintenance Management Software
CTC	Crush, Tear, Curl
CUMF	Cumulative Frequency
DET	Detection Rating
DOD	Department of Defence
DP	Discursive Psychology
EBQ	Economic Batch Quantity
EPZ	Export Processing Zone
FMEA	Failure Mode and Effect Analysis
FMECA	Functional Failure Modes Effects and Criticality Analysis
FTA	Free Trade Agreement
I&C	Instrument and Control
JIT	Just-In Time
KTDA	Kenya Tea Development Agency Factory
KWH	Kilowatt Hour
MCMC	Monte Carlo Markov Chain
MPM	Maintenance Performance Measurement
MTBF	Mean Time Between Failures
MTBF	Mean Time Before Failure

MTTF	Mean Time to Failure.
MTTR	Mean Time to Repair.
NHPP	Non-Homogenous Poisons Process
NIST	National Institute of Standards and Technology
OCC	Occurrence Rating
OEE	Overall Equipment Effectiveness
PDM	Product Data Management
PM	Planned Maintenance
RAMS	Reliability, Availability, Maintainability
RBI	Risk Based Inspection
RCFA	Root-Cause Failure Analysis
RCM	Reliability-Centred Maintenance
ROFA	Return on Fixed Assets
RPN	Risk Priority Number
SEV	Strategy Execution Valuation
TF	Term Frequency
TPM	Total Productive Maintenance
TQM	Total-Quality Management
TR	Threshold Regression
UK	United Kingdom
VED	Vital Essential and Desirable
VIKOR	Vlekriterijumsko KOmpromisno Rangiranje

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Tea industry is a vibrant and multifaceted sector that plays pivotal role in economies, cultures in diverse societies world over. It has a noble significance dating back to centuries. Tea contributes immensely to global economy generating substantially in world economy through cultivation, processing, distribution and retail sales. It is a vital source of income and employs millions of world population particularly in tea-processing regions. Tea is produced in various regions around the world, with notable production hubs in countries like China, India, Sri Lanka, Vietnam and Kenya accounting for highest percentage of global tea. In Kenya, plantations are domiciled in the Highlands of Central Kenya, Kericho, Nandi and Kisii. The global tea market offers array of tea varieties each with distinct flavor profiles, Processing methods and cultural orientation. Common types of tea include Black tea, which is fully oxidized and with robust flavor. Green tea, minimally processed and prized for its freshness particularly for health benefits and finally herbal tea which is made from infusing with spiced herbs. The processing commonly starts with plucking of raw tea from farms and transporting to the industry for processing.

On arrival to factory, freshly plucked tea leaves is withered to allow them lose moisture and become supple. The leaves then undergo CTC, where rolling, breaking their cell walls to initiate oxidation. Spreading in Continuous Fomentation Unit where the leaves oxidize, transforming from green to brown and developing the characteristic flavour. Firing in drier halts oxidation and reduces moisture, preserving tea qualities. Finally, the tea is sorted by size and quality before packaging.

Each processing unit has some associated maintenance considerations to ensure they are efficient, effective and with minimal downtimes. All procedures required to keep something in or return it to a functional state are referred to as maintenance (Moldovan & Magyari, 2022).

1.1.1 Preventive Maintenance Contribution to Profitability

The financial return on a company's fixed assets (ROFA) is a significant factor in estimating a company's investment value. Asset management is focused on attaining the lowest total cost across the course of production or provision of a desired service. To manufacture goods or services at a cheaper cost than rivals, one must outperform them in terms of ROFA (Jin, Mai, and Cheung, 2022). Because maintenance costs make up a sizable portion of production costs, maintenance management has an impact on ROFA. Jihong Yan (2015) pointed out that when maintenance costs as a share of manufacturing costs change, it is important to look at maintenance effectiveness to determine the reasons behind the change.

This study examine how ROFA may be realized through optimization of maintenance performance measurement of critical machines in tea processing, focusing more on Litein Tea Factory in Kenya. Litein Tea Factory is one of the oldest factories in Kenya having been commissioned in 1966. It currently serves 8,849 small-scale tea farmers who are also factory shareholders that supply green leaf to the factory for processing into CTC black tea.

1.2 Current Maintenance Activities in Tea Industry

In maintenance, it is important to replace a reactive-linked culture with a proactive reliability-focused culture to enhance cost reduction. Hooi and Leong (2017) argued that when proactive measures are used, they guarantee less human effort and minimal energy waste during maintenance and repairs, increasing profitability. Preventive maintenance grew to become more valued in the tea sector to cut costs associated with equipment upkeep and increase availability (Alhilman & Abdillah, 2019).

1.2.1 Downtime

Equipment uptime increase aims to lower costs. To close the difference between ideal and actual costs, a pro-profit strategy is required. Lean total-quality management (TQM) and just-in-time (JIT) implementation issues can easily result in an increase in downtime. Therefore, it is highly desirable to apply reliability-cantered maintenance (RCM) and total productive maintenance (TPM) as corporate-wide upgrading methods. Due to the costs associated with lost sales because of products not being produced in a timely manner, idle operations staff and production, late deliveries, overtime required to make up for missed production in order to meet delivery commitments on time, downtime raises the industry's financial expenditure (Tabikh, 2014).

1.3 Problem Statement

Litein Tea Factory produces an annual average of 5,025,504 kg of made tea with an energy consumption of Ksh.108 million, cost of spares being Ksh.2.76 per kg of made tea, maintenance cost of Ksh.3.63 per kg of made tea, labour cost of Ksh.1.2 per kg of made tea and production cost of Ksh.89.33 per kg of made tea. The costs of electricity, maintenance, spares and labour translate to 24%, 4%, 3.3% and 1%, respectively. However, little has been done on equipment maintenance and replacement, which contribute substantively on production costs stemming from repairs and spares, retrofitting, downtime, machine reliability and availability. Tea factories face inefficiencies and lack optimization leading to potential productivity losses and increased operational costs. The gap highlights the need for comprehensive optimization framework to capture the overall effectiveness and efficiency of maintenance activities.

The current study aimed to address the research gap in literature and to determine the optimization of maintenance performance measurement of critical machines in tea processing with focus on Litein Tea Factory, Kenya, aimed at improving equipment reliability and enhancing overall operational efficiency.

1.4 Main Objective of the Study

Optimize maintenance performance measurements of critical machines in tea processing: a case study of Litein Tea Factory.

1.4.1 Specific objectives of the Study

The study was guided by the following specific objectives:

1. Identify a critical equipment in tea processing plant.
2. Evaluate a maintenance model for the critical equipment in tea processing plant.
3. Optimize the maintenance model of the critical equipment in tea industry.

1.5 Justification of the Study

The analysis of downtime, throughput, failure type, operating time, service time and number of failures provide insight for policy and practices in optimization of maintenance for enhanced productivity in tea processing. This practice enables factories to strike appropriate balance between reliability, availability and maintainability on achieving optimum process maintenance parameters. As a result, tea companies reduce maintenance costs for the processing equipment as well as ensuring equipment stability and timeliness in production. When the maintenance parameters are optimized, overall maintenance of equipment translate to optimization of production time, efficiency and effectiveness in the entire process thus enhancing reliability and availability in production unit.

1.6 Organization of Thesis

The thesis is designed to have 8 chapters where chapter on is on general introduction.

Chapter 2: Literature Review - Reviewing relevant literature on maintenance performance measurements in industrial settings and their methodologies.

Chapter 3: Methodology - The chapter describes research methodology adopted for the study including data collection methods, sampling techniques and analytical approaches.

Chapter 4: Results and Discussions - Interpretation on findings in light of research objectives and relevant literature, theoretical frameworks and relevant literature are given insights.

Chapter 5: Conclusions and Recommendations - The chapter summarizes the main findings of the study and drawing best practices for the study along with suggesting directions for future research.

The adopted referencing in all citation made is American Psychological Association (APA) and Plagiarism test carried out and certified on verification that the similarity index is below 25%.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of literature related to maintenance performance measurements. The chapter begins with a review of literature on related concepts such as maintenance performance measurement system, analysis of reliability, availability, maintainability and safety. The section then examines literature on black tea processing production parameters, Criticality Analysis (FMECA) and Functional Failure Modes Effects. The next sections explore the development a predictive model and the factors constituting the input parameters for predicting tea industry's productivity. This section then followed by a review of the literature on reliability-cantered preventive maintenance planning for an ongoing system that is deteriorating. The chapter then explores existing works on optimization maintenance, model formulation and optimization, and how offshore production firms can capitalize on maintenance optimization for improved performance.

2.2 Maintenance Performance Measurement System

According to Parida (2006), maintenance performance measurement (MPM) helps determine the maintenance associated value to justify decision to make the investment and revising resource allocation where necessary to meet the expectations of customers and address environmental, health, and safety concerns to accommodate organizational structural changes and new operation and maintenance trends. As a result, the Author defines the MPM as the multidisciplinary process of evaluating and justifying maintenance investment value and taking care of the demands of the organization's stakeholders as seen strategically from the standpoint of the broader business. Performance indicators, according to Parida (2006), should be part of an empirical investigation of how the maintenance function interacts with other organizational functions, which are portrayed as the production functions. According to this point of view, specific guidelines must be established before maintenance functions can be chosen as performance indicators. Maintenance performance measurement pointers establish a connection between the maintenance objectives, actions, and results as well as how maintenance objectives interact with processing and corporate objectives. As a result, it is necessary to identify performance metrics for the maintenance process and outcomes for each cluster.

According to Swanson (2001), the cost performance, leading, and lagging indicators can be used to quantify maintenance performance. In order to achieve the required production outcomes, the maintenance leading indicators thus keep an eye on the jobs that are being carried out. The study continues by saying that the following steps are taken to address the maintenance process: work identification (based on maintenance objectives and performance gaps); work planning; work scheduling; and work execution. Proactive maintenance is calculated as a percentage of reactive and improvement activities as well as the rate at which work requests are answered. Work planning is a gauge for planning quantity, quality, and reactivity. The scheduling of tasks includes the execution of the plan and its quality. Finally, job execution measures things like schedule adherence, MTTR, work order turnover, and manpower usage and manpower efficiency.

Swanson (2001) and Parida (2006) both agree that the technical systems' dependability, availability, and operability may be summed up as the results of the maintenance process (lagging indications). In these, the evaluation counts the failures, counts their frequency, counts the MTBF, counts the availability, and counts the overall effectiveness of the equipment. Additionally, these writers point out that maintenance effectiveness and efficiency is influenced by maintenance costs by a factor of times. Direct maintenance costs, percentage cost of supplies, maintenance stock turnover, breakdown severity, percentage cost of staff, maintenance intensity are the factors that make up cost performance.

Hansen (2002) examined equipment effectiveness, focusing on increased profit when using powerful maintenance tool. The results of the study illustrated Overall Equipment Effectiveness (OEE) as a measurement method effective in giving the understanding of the performance of the manufacturing area, together with the conceivable weaknesses. OEE computes the manufacturing process effectiveness percentage and other factors, namely availability, quality, and performance efficiency.

Maintenance management, initially, was undertaken in response to engine failures but it was retaliatory. Breakdown maintenance falls within this area as it is done after a machine malfunctions. According to Parida and Kumar (2007), breakdown repair has obvious drawbacks, including production process disruptions, operator risk, and more severe damage. The other strategy is proactive maintenance, which Ding and Kamaruddin (2015) noted helps in removing the source of failure. According to Swanson (2001), maintenance increases system reliability and availability while extending system effectiveness and life. According to Ahuja and Khamba (2008), pre-operational maintenance encompasses a variety of tasks including preventive replacement, quality control, regular and periodic inspections, work planning, condition monitoring, people management, purchasing and material management.

2.3 Effect Analysis of Reliability, Availability, Maintainability and Safety

High operation and maintenance costs can only be reduced by embracing continuous improvement in the areas of reliability, safety, and quality. Failure risk is seen as a factor of reliability, maintainability, availability and safety. Improving the reliability have effects on level of Mean time between failures. Ebrahimi (2010) claims that increasing sub-system thrusters from 200,000 to 300,000 hours and MTBF from 90,000 to 150,000 hours and can increase the system's overall dependability by 5% up to about 80 % and maintainability by 6% up to 71%. High failure risk reduces costs during the vessel's operational period. However, it should be noted that due to technical and financial considerations, improving the MTBF for these two subsystems cannot be accomplished by introducing redundancy. Accordingly, design changes and a reduction in human error rates are primarily advised as an alternative method to increase system reliability (Ebrahimi, 2010).

Plant maintenance aims to ensure systems run at low cost in order to improve the operation efficiency meant at satisfying plant operational needs. The mining industry maintenance costs have remained unchanged over time. For over ten years, they have averaged between 25% and 45% of operating costs (Campbell *et al.*, 1997). Some of the contributing variables could be larger production rates, higher availability requirement, increasing equipment size, and rising equipment complexity (Ebrahimi, 2010). It is important to note that maintenance costs constitute a key factor that determines profitability. Industrial professionals and researchers believe that diminishing maintenance costs and enhancing operational efficiency could improve operating equipment maintainability, reliability, and availability (Barringer, 2004, 2006; Crow, 1994, 2005; DOD, 2006; Hall, 1997; Kumar, 1990; NIST, 2006).

Many authors have given different definitions of maintenance, and these definitions have changed over time. Industrial maintenance has changed over the past 50 years from being a non-issue to a strategic priority for the corporation (Kobbacy *et al*., 2008). They include condition determination, overhaul, repair, modification, servicing, and inspection. Industrial plants and equipment are expensive, especially when their procurement involves foreign exchange. As such, proper maintenance of plant and equipment constitutes one way to minimize on industrial costs. Poor maintenance of equipment can result in economic losses owing to increased down time, poor efficiency and deterioration. Optimal maintenance strategies for industrial equipment, when properly designed and implemented, help mitigate system failures to improve system reliability thereby reducing maintenance costs. Any industry's maintenance expenses make up a sizable amount of overall spending (Ravichandran & Mahindrakar, 2010).

With proper maintenance, this challenge may be worsened by modern equipment sophistication and increasing complexity revolving around new engineering support difficulties, all of which exert stress on maintenance (Mishra & Pathak, 2012). All efforts to optimize in this regard result in significant savings. The entire equipment life cycle must be considered when planning optimization. For maintenance prevention, optimization efforts are done at the conceptual stage. When maintainability and reliability are properly "traded off" throughout the design and development phase, as well as when optimal redundancy is built in, maintenance costs tend to be reduced for the desired degree of equipment stability. Plant, maintenance store, and equipment standardization provide additional opportunity for optimization as highlighted by Antoniolli *et al*. (2017). A balance between breakdown and preventative maintenance during the "in service life," and regular and effective training of maintenance staff, can help save maintenance expenses.

2.4 Black Tea Processing Production Parameters

In order to understand how maintenance procedures, affect manufacturing performance in KTDA-managed plants, Ng'era (2013) conducted a study. According to the report, preventative maintenance accounts for 76% of the maintenance performed in KTDA factories, and breakdown maintenance accounts for 20%. According to the survey, factories' plant availability ranges between 46% and 88%. The percentage of plant availability and preventative maintenance also showed a significant correlation. The study also found a link between plant availability and the proportions of breakdown repairs that are performed. The study discovered a link between firewood usage plant availability, KGMT/CUMF, and auction price. Plant availability and thermal energy assessed in MJ/KGMT, energy cost per kilogram of tea produced, and KWH/KGMT all correlated negatively. Ng'era further noted that in addition to individual capabilities, technical capability, resource allocation, maintenance performance and task design is influenced by a number of other variables. According to the study, in order to deal with production disruptions, tea manufacturers should invest in redundant equipment and build buffer stockpiles.

Bulali (2014) did research to determine energy efficiency in black tea processing. The study sought to explore how the age of processing machines influences energy utilization efficiency in KTDA-managed black tea processing factories. Census of data for the earmarked period of study were taken. Age of machinery in a factory provided an indirect mode to assess energy efficiency performance both in more modern and less modern technologies. Mixed results from all the regional clusters on the correlation between age of processing machines and energy efficiency was evident with clusters A, C and D. This observation suggested a weak positive correlation between the two variables. Meanwhile, weak negative correlation was observed in clusters B and E, despite them being situated in far flung geographical regions apart. However, a moderate negative correlation was observed among the factories within cluster F. From the research, the age of processing machines that represent modern technology could not portray visible influence on energy efficiency comparatively to the older factories on contrary showing better energy utilization efficiency. The research conclusively pointed out the possibility of the age of processing machines being an insignificant factor in determining energy efficiency within the sample population. On exhausting all the technical potential for energy efficiency effectively, improvement in energy demand sectors, this growth can be limited to 8%.

Bulali (2014) also sought to determine the extent of the influence of technical staff energy awareness on energy efficiency. Respondents in all the 7 geographical clusters scored above 95% on the level awareness on the energy efficiency measures recommended by KTDA. The empirical analysis of the variables yielded a very weak negative correlation (r=-0.0669). It was concluded that the apparently high level of awareness among technical staff had no influence on the energy efficiency among the target population. The study observed that previous studies found no significant relationships in their study of energy efficiency on similar variables. Relationships between energy efficiency behaviour and awareness have generally been weak and often contradictory. No significant relationship has been reported between energy efficiency awareness and energy efficiency. It is generally expected that education and energy conservation and efficiency would be positively correlated. However, as Bulali notes, majority of studies have found mixed results. Therefore, more research should be carried out to establish why the two variables are not positively correlated as expected.

2.5 Criticality Analysis (FMECA) and Functional Failure Modes Effects

It is important to note that classical Reliability Centred Maintenance (RCM) focuses on the functional failures of systems and components. In order to determine the functions of physical assets, failure modes, consequences of failure, their significance and, consequently, their criticality, a systematic process is used, according to International Atomic Energy Agency's (2008) report on the application of reliability-cantered maintenance to optimize operation and maintenance in nuclear power plants. This approach is referred to as a failure modes effects and criticality analysis, or FMECA, in its most full form. A streamlined version of the procedure called FMEA has traditionally been utilized in the electricity, gas, and automobile industries. Some utilities have created checklists that are intended to adhere to the process' logical steps without specifying each one in detail. The assessment of the effects of equipment failure is aided by checklists. The checklists imply that the influence of system functions and the failure modes of the apparatus are recognized.

2.5.1 System Functions

Each and every physical item has a job to do. In order for those assets to continue serving their intended purposes, upkeep is necessary. The functionalities of the chosen system must be defined as part of the RCM process's first analysis stage. The system components, flow pathways, and interactions can be represented using straightforward schematic diagrams. Physical assets typically have a main use, which is frequently indicated by the name of the asset, such as "condensate extraction pump." Although they are more difficult to spot, secondary functions are crucial to the RCM process's success. As an illustration, a secondary purpose of an auxiliary boiler might be to heat the factory while its major purpose might be to deliver steam to a crucial production process.

2.5.2 System Functional Failure

There must be at least one functional failure mode or mechanism for each function listed. The mechanism of the function's failure and its effects are described in the functional failure statement.

2.5.3 Identification of Equipment

Identification of every piece of equipment whose failure potentially led to a functional failure is necessary for the analysis procedure. Tracing the function's flow pathways enable proper identification. Valves, pumps, filters, heat exchangers, tanks, and other mechanical (rotating and stationary) equipment must be mentioned. Similar identification is required for electrical equipment, including motors, circuit breakers, and relays, as well as all related Instrument and control (I&C) equipment. It is crucial to determine the equipment's type as well as its specific use within the system under consideration. The analysts may be able to find pertinent data by using a larger equipment reliability database thanks to this technique.

2.5.4 Identification of Failure Modes

Analysts refer to the inability of a component, such as a valve to open or close or a pump to start or stop, as having "failure modes" since they define the failures' nature rather than their causes. Typically, reliability and probabilistic safety analysis (PSA) employ this straightforward description of failure mode. In the normal course of things, maintenance professionals would go further and explain why the failure happened, such as valve spindle wear, actuator flaws, or in the case of pumps, related switchgear flaws. The latter concept of failure causes is more similar to that of a safety analyst, and the definitions of failure mode used in the RCM process usually match those of safety analysts. While "failure causes" often refer to the degradation mechanism that results in a failure mode, "failure mode" is used to describe circumstances in plants such as failing to open or close.

2.5.5 Identification of Failure Effects

The analysts must determine how functional failures affect safety, the environment, worker safety, and plant efficiency. The created list must include all the data the analysts needed in order for them to create appropriate countermeasures to lessen the effects. For instance, what are the implications of failure, how will failure be discovered, and what repair alternatives and preventative measures are available.

2.5.6 Criticality

A component is deemed critical if the facility cannot tolerate the impact of its failure. A component might be considered critical in a nuclear power plant, for instance, if a breakdown results in any of the following: The failure results in a number of things, including: the need to shut down before regularly scheduled outages or a reactor trip; a decrease in efficiency/power; technical specification limit breach. Other failures are high personnel safety risk; a breach of environmental release limits; significant damage, and release of radiation to the public. In cases where redundancy is present in a system, the evaluator should be given credit for it when determining criticality. For instance, neither pump would be regarded as important in an application with two 100% capacity pumps (which could be utilized alternately) because it is logically assumed that if the operational pump failed, the other pump would be available and used. It is vital to note that the analyst only considers one failure in this case, which is why it was assumed that the second pump would be functional. The flow switch or pressure intended to ensure that the standby pump would activate in the event that the duty pump failed would be regarded as crucial in such a scenario. Additionally, it might be able to give a component function via other components rather than just a different train of the same thing. Even though it is not strictly a "redundant" valve in the design, another valve in the system may be able to provide the "function" of the first valve.

2.6 Developing a Predictive Model

In their study, Mondal *et al*. (2016) sought to develop a predictive maintenance in India manufacturing services. They used different models with no investment on technological component to establish an integrated framework for predictive maintenance of plant/machine. The models applied a modified failure mode and effect analysis (FMEA) on a unit that extracts palm oil. According to the findings, machine downtimes were decreased by 39.13%. The second model used failure mode effects and criticality (FMECA) analysis, which revealed a 537.7-ton annual increase in the production of the coal pulverizing mill. When implemented to an overhead crane in a steel manufacturing facility, Model 3's failure mode and effect criticality analysis (FMECA) and non-homogenous poisons process (NHPP) showed savings of Rupees 168,985.92 annually. When Model 4 (integrated NHPP model and system availability concept) was put into practice at a wheat flour mill, it decreased the frequency of general maintenance, which in turn decreased maintenance costs for the business. The research also recommended that more research be conducted to increase the robustness and applicability of the integrated framework for predictive maintenance that has been developed.

Due to high operation and maintenance costs in the offshore industry, Ebrahimi (2010) investigated into the effects analysis of maintainability, reliability, and availability parameters in design and operation. This analysis is in coming up with lower operation costs. When maintainability, reliability, and availability, and safety are taken into account along with failure risk prices for these kinds of structures, the dynamic positioning system is one of the most important sub-systems in the research. Utilizing Failure Mode and Effect Analysis and Reliability Cantered Maintenance together proved the most appropriate in identifying the probable events and accidents and associated consequences. According to the research, the reference positioning subsystem has a greater probability of failures, which can cause safety issues and a substantial level of reliability. Operational repercussions and function loss were the main effects of the other subsystem failures. The findings clearly showed the value of redundancy in many subsystems for reducing the consequences of failures from safety concerns to manageable economic implications. In addition to the analysis mentioned above, the reliability block diagram method was developed as a quantitative tool for the system to calculate the quantity of reliability, maintainability, and availability with the recommended subsystems in addition to elucidating the proportion and impact of each subsystem on the system's overall reliability. It was also derived from subsystem reliability tables that Resilience, Integrity and Optimization (RIO) cards and thrusters have a significant part in enhancing the overall system's dependability in accordance with their level of Mean Time Before Failure (MTBF). To improve overall system reliability by 5% up to about 80% and maintainability by 6% up to 71%, the MTBF of these subsystems for the RIO Card can be increased from 90,000 hours to 150,000 hours and for the thrusters from 200,000 hours to 300,000 hours. That entails a substantial cost decrease during the vessel's operational period due to high levels of failure risk.

By using normal alarm limits, the levels of which are periodically adjusted based on factors like operational experience, machine supplier recommendations, prior failure data, or national and international standards. A predictive model was then developed to determine whether a potential failure problem exists. However, it was discovered that some battle collars had alarm limits that, if set too high, might cause a machine to fail without giving cautionary signal. In contrast, if the machine's limitations are set too low, it will succumb to false alarms, which may delay the occurrence of a true warning until it is too late. Experienced machine operators and maintenance specialists have acquired the ability to differentiate between actual and false alerts over time. However, it was discovered that such knowledge could not be available constantly, necessitating the necessity to simulate such circumstances. The creation of a failure prediction model, which was difficult to build, became essential for attempts.

The following 3 issues are those that practitioners of condition monitoring frequently run into: establishing reasonable boundaries for identifying when to check on the machinery again and estimating the next time to replace or repair it when problems start to show. The theory's main tenet is the presumption that a machine's life may be separated into two distinct regions, namely a stable zone and failure zone, which can be established based on the measured measurements of observed state.

When a machine has a problem, condition monitoring can alert the operator and with enough practice, pinpoint the exact cause. However, it is more challenging to estimate the machine's remaining life quickly after the issue has been discovered and to determine when to replace or repair the unit. The majority of the remaining life prediction research has focused on models with great mathematical complexity or reliability. There is undoubtedly a need for a straightforward, industrially relevant systematic prediction model. In this essay, the creation of a model intended to implement such a strategy is discussed. Stable zone and failure zone are the two regions into which condition-monitored measures have been split. A reliability-based approach is used since condition measurements are consistent with being in the stable zone. Reliability data and condition-monitoring data are combined to forecast the remaining machine life when condition measurements reveal the presence of a problem. To evaluate the model's effectiveness and draw attention to some of its implementation challenges, both simulated and real case studies were examined. It is crucial in this study as it is clear that the prediction model depends on the reliability and precision of the condition-monitored measurements. The model is anticipated to result in a more methodical approach to evaluating the risk of machine failure. This analysis is primarily applicable in most condition-monitored situations, where the failure lead time is sufficient to provide an indication of the condition-monitoring measurements to correspond to the machine's true health. However, based on other external elements including timing, criticality, environmental impact, cost, safety, and spares, the final maintenance action selection is thus inevitable.

Evaluation of equipment maintainability, reliability, and availability in oil and processing plant analysed on the modalities for approximating the next plant equipment failure time. There are 3 proposed ways of estimating the next failure time based on vibration: Markov model-based, Regression model-based and the Hybrid approaches.

The finite state continuous time Markov model theory can be used to predict when a gas compressor would fail next. The linear regression model utilizing moving average filter has been proposed in the regression model-based approach. The hybrid strategy combines the best elements of both strategies. Using computational experiments and case studies based on shaft vibration sensor data, it was possible to estimate the next failure time based on the vibration level. Since the degradation model of mechanical systems appears to be more appropriately represented by an exponential model, the first advantage to take into account a more complex regression model rather than a first-order linear regression model was undertaken. Secondly, the failure is monitored by vibration signals, and the linear regression model may be improved to a more elaborate regression model by taking trade-offs into consideration. Thirdly, it is feasible to detail the techniques by taking into account the equipment operating mission profile and the division of the ocean environment. Various uncertainties cause the deterioration process to change over time. Real-time update consideration was made utilizing techniques like Monte Carlo Markov Chain (MCMC) and the traditional control model (Goode1 *et al*., 2014).

Failure Mode and Effects Analysis (FMEA) is compared to calculating the probability of failures, according to Reliability Management of Manufacturing Processes in Machinery Enterprises. Transfer information from the FMEA to the Bayesian Belief Network (BBN), then analyse the system and put corrective measures into place. Utilizing BBN allows for reliability prediction. Contextual analysis can be used to generate reliability (the BBN's output) dependent on the values of the input variables. The technique used to communicate data from the reliability analysis system to the decision-making system is crucial during the research process. A practitioner's work is made easier by the model's automated failure and probability transfer from FMEA to BBN.

An analysis of the manufacturing process was conducted to produce the following sequential steps for managing the reliability of manufacturing processes in the equipment industry:

FMEA is enhanced; severity and detection parameters are specified based on expert evaluation, and the classifier is elaborated.

The method for automatically transferring data from the FMEA to the BBN is described hereunder:

BBN is helpful in making decisions regarding the choice of corrective activities.

Decision assistance from BBNs is gained in the form of reliability management, and decision support is provided by BBNs via scenario analysis.

The importance of research to science and the economy; cost savings and improved output result from deployment. A manufacturing method that promotes waste minimization and sustainable consumption and production is realized as a significant corporate strategy in the worldwide industry (Kostina, 2012).

In order to lower the expense of preventative maintenance, it is necessary to look into and purchase a technology that addresses or lessens persistent equipment issues. Predictive Maintenance (PDM) inspections ought to be planned and scheduled using the same methods that are effective for scheduling Preventive Maintenance (PM) tasks and integrating all data into the Computerized Maintenance Management System (CMMS).

To develop the equipment maintenance plans required for every physical asset that maintains its objectivity in working situations, reliability-centred maintenance employs structured processes. The major goal is to come up with critical components in processes based on the available information, customized design on preventive/predictive maintenance strategy. Another important tactic based on prior failures is root-cause failure analysis (RCFA). The RCFA is intended to take remedial measures that go beyond the component stage and address the system's shortcomings. TPM emphasizes people as a crucial component of TQM. It focuses on how maintenance work is organized using the following methodology:

- Autonomous operator maintenance, in which an operator assumes responsibility for the basic maintenance of his or her plant, helps the operator develop a rational sense of ownership.
- Clearly stating tasks like routine maintenance, lubrication, adjustments, small repairs, and the orderliness and cleanliness of his or her workspace.
- Enhance the operator's abilities and expertise to maximize operational efficacy.
- The operator's mobilization to look for any early indications of wear, degradation, misalignment, oil leaks, stray chips, or loose parts. Make improvement proposals to reduce losses brought on by the plant performing below par or breaking down.
- To enhance the performance of staff and equipment, use cross-functional teams made up of operators, maintainers, engineers, and managers, create a timetable for cleaning up and PM that extend the plant's life and increase its uptime.

- Top management must exhibit their commitment to the policy by dedicating enough time and allocating enough resources to bring about and maintain any necessary cultural changes and to train staff in autonomous maintenance.
- Consideration of financial optimization, integrates statistical analysis with all pertinent information about asset, focused particularly on the expenses associated with downtime, maintenance, lost productivity, and subpar final products.

Data is then compared to financially advantageous decisions as follows:

- When should equipment be taken offline for maintenance?
- How economically viable is it to repair or replace an asset?
- How many vital replacement parts should be readily available at all times?

Precision in data analysis is important for financial optimization because erroneous decisions could have a negative impact on a company's ability to compete. Incessant Improvement refers to the continuous search for better ways to carry out a task and is defined by identifying constructive radical enhancements to current procedures. Re-engineering will be the main focus, disregarding current practices in favour of creating fresh approaches to carrying out the assignment. Best-practice benchmarking with a focus on the maintenance process is one of the primary instruments for accomplishing continuous improvement aimed at enhancing an organization's competitiveness.

It has been discovered that organizations with intelligent maintenance cultures typically experience reduced operating expenses relative to the cost of the final product and ultimately strong returns on investments. According to the results, it is advised that businesses invest in highly dependable machinery with reasonable maintenance costs. The benefits of dependable, long-lasting equipment go far beyond just reduced maintenance costs. For instance, smaller inventories of spare parts and fewer (but usually more highly multi-skilled) operators and maintenance staff are needed. It is essential to provide an extensive and simple-to-use database for behaviour analysis, benchmarking, and continuous system development. According to research, downtime costs the majority of large organizations between 2 and 16% of their yearly sales. Generally speaking, at least 20% of downtime expenses are attributable to human error and complacency. This study can be greatly enhanced by employing only individuals who have received the right training as well as by creating and implementing appropriate information-technology controlled processes, resulting in more proactive service (Ojukwu, 2006).

In their survey of several companies, Kumar and Mondal (2016), who are experts on the development of predictive maintenance in India's manufacturing sector, found that while there are a number of obstacles to adopting a predictive maintenance policy, their study found that high costs are the main deterrent. In developing the predictive maintenance framework for industrial enterprises in India, a number of predictive maintenance models without a technological component are considered as shown in Table 1.

Table 1: Showing Predictive Maintenance Models Developed

Model	Companies	Models used	Description
modified FMEA	Palm oil extraction unit	Failure mode and effects analysis (FMEA)	FMEA sheet is modified with an additional column, for developing an output range to predict the occurrence of failure modes.
Model modified FMECA	Coal pulverizing mill in a thermal power plant.	Failure mode, effects and criticality analysis (FMECA)	FMEA sheet of model 1 is modified by adding another column incorporating the criticality of each component.
Model integrated FMECA and NHPP	Over-head crane in a steel manufacturing company.	FMECA and non-homogenous Poisson process models. (NHPP)	Integration of FMECA and NHPP models. In this model, the most critical component is identified using FMECA. MTBF is calculated for the critical component and compared with the threshold MTBF.
Mode NHPP models and system availability concept.	Wheat flour mill	NHPP models and system availability concept.	Component failure data is fitted with NHPP model and system availability is calculated. Compared with threshold availability (A(Th)) to predict overall maintenance time of the system.

According to Table 1, using a modified FMEA method to predict the occurrence of certain failure modes is known as predictive maintenance. The occurrence of any failure mode is noteworthy when there is a change in the output or production rate, which may fluctuate within a range with upper and lower limits. The output or production rate is suggestive as a predictor to foretell the occurrence of any failure mode. The developed framework involves the subsequent steps:

Step 1

The proposed methodology's first phase involves gathering the failure data produced by each downtime event.

Step 2

Mod-FMEA analysis is used to determine the output range for each failure mode from the failure data gathered in step 1. As part of the Mod-FMEA process, components, assemblies, and subsystems are examined to identify failure modes, causes, and ranges of outcomes for these failures. It's crucial prerequisite for interval calculation is the estimate of mean changes from sample to sample. Rather than estimating the mean as a single value, a confidence interval with an upper and lower limit is produced and stated in terms of the confidence coefficient. The percentage of samples of a certain size that may be anticipated to contain the true mean is essentially what is being described in equations 2.1 and 2.2. They are all appropriate for sample sizes greater than or equal to 30 for t-tests but fewer than or equal to 30 for z-tests. In order to calculate the output range, formulas in equations 2.1 and 2.2 are applicable.

For (n ≤ 30) formula used

$$\bar{x} = \pm t_1 - a_{2,}\, n - 1 \times \left({}^{s}/_{\sqrt{n}} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

For (n > 30) formula used

$$\overline{x} = \pm Z_1 \bar{x} = \pm Z_1 - a_{2,}\, n - 1 \times \left({}^{s}/_{\sqrt{n}} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.2$$

Step 3

The output range obtained in step 2 is compared with the system's output that is being constantly monitored in this phase. If the value of the constantly monitored output deviates from the expected range of output, the system looks for the failure mode that the measured output falls under, identifies the failed component, and starts the maintenance procedure. After maintenance, the failure database is updated, and the process begins again. VIKOR methodology "Vlekriterijumsko KOmpromisno Rangiranje" a Serbian term standing for "Multi-criteria optimization and compromised solution” pointed out that preventive CTC unit, condition-based and fermentation unit maintenance are appropriate maintenance applications. Monte Carlo Simulation is used to simulate the period for preventive maintenance.

Production losses caused by downtime eventually result in financial losses. Currently, the organization employs a corrective maintenance plan. Corrective maintenance plan is ineffective for important machinery in the tea sector, according to an analysis of the findings from the selection of the maintenance strategy using Analytical Hierarchy Process (AHP) and VIKOR. The tea factory performs and analyses Failure Mode and Effect Analysis (FMEA), where causes and consequences of failure modes are identified. Each failure mode's Risk Priority Number (RPN) is calculated using equation 2.3:

$$RPN = Severity \times Occurrence \times detectability \quad \text{......................................} \quad 2.3$$

Based on grading scales that group the machines in the tea factory as vital, very important, important, and least important utilizing vital essential and desirable (VED) analysis, it is possible to determine the severity, occurrence, and detectability. The classification of machines is done using a five-scale rating. A machine is rated as vital if it received an 80 or more, extremely important if it received a 60 to 80, important if it received a 40 to 60, and least important if it received a score of 40 or lower. According to Srivastava and Mondal (2014), crucial devices include the heat exchanger, fermentation conveyor, drying conveyor, and rotor-vane.

Stage 4

When choosing a maintenance strategy for critical machines with a risk priority number (RPN) greater than 100, an analytical hierarchy method is integrated with VIKOR. For the Rotor-vane, CTC machine, and fermentation unit, separate maintenance techniques have been chosen. 4 criteria are used to choose maintenance plans. A questionnaire was used to collect data. The information needed for AHP was gathered from 3 experts. Preventive maintenance, condition-based maintenance, corrective maintenance, and autonomous maintenance are all taken into consideration. Criteria used encompass value added, cost, equipment, technology, and safety.

The following are the steps of the integrated AHP-VIKOR technique for choosing a maintenance strategy: Establish a panel of specialists: Create a hierarchical model for the chosen criteria and compute the aggregated weights of the criterion using the AHP approach. The relative weight of each criterion is determined using pair-wise comparison; the opinions of all experts will be combined and a weight for each aggregative criterion will be determined using geometric average. Each criterion's weight is determined using the heuristic technique of an arithmetic average. That's why Start by adding the arrays in each column. Then, to create a normalized matrix, each array in each column is divided by its corresponding column sum. Finally, using Monte Carlo Simulation, the maintenance interval for the Rotor-vane and fermentation unit for the following year is predicted. Time between failure of each machine and its frequency are gathered from records from the previous year, and their probabilities of occurring are computed using a binomial distribution. As illustrated in Table 2, Preventive maintenance intervals are simulated for the following year using cumulative probabilities that have been determined and split down into a random number range. The Table below displays the simulated maintenance interval for the following year.

Table 1: Simulated Maintenance Interval for Next Year

Month	Random Number	Maintenance Interval
Jan- Mar	25	6
April-Jun	39	7
July-Sept	65	8
Oct-Dec	76	8

2.7 Production Factors for Calculating the Tea Industry's Productivity

According to Gupta and Dey's (2010) productivity model for the tea industry, labour input (L), capital input (C), material input (R), energy input (E), subsidy ration input (S), and other input (Q) are the production factors that make up the input parameters for calculating the tea industry's productivity. (Qt) The amount of tea produced is the total production. The productivity measurements appropriate for the tea business are derived by entering these inputs and outputs into the productivity accounting model as shown in equation 4:

$$\text{Total productivity} = Qt \div (L+C+R+E+S+Q) \quad \text{........................ ....} \; 4$$

In order to maintain quality, all values in the updated model that relate to output and inputs are expressed in monetary equivalent and deflated to a base year using a suitable price index or an average inflation rate. Terminologies used in the proposed model that are unique to the tea business could be defined as: Final Product (Qt): The output (Qt) is a monetary representation of the total amount of manufactured tea sold. Gupta et al. (2015) developed a methodology for measuring productivity in the tea sector.

2.8 Preventive Maintenance with a Focus on Reliability Scheduling

According to Zhou (2008), in engineering, a sequential imperfect preventive maintenance policy results in a decreasing succession of maintenance intervals. Whereas condition-based predictive maintenance (CBPM) techniques offer an assessment and prediction of the system condition based on the data gathered through continuous monitoring. In the study, the sequential imperfect maintenance strategy is attempted to be integrated into CBPM. For a system that is susceptible to degradation because of the poor maintenance, a reliability-cantered preventative maintenance strategy is suggested. Two improvement elements are used to construct a maintenance model. An incomplete PM is run on the system when the reliability approaches the threshold R. At the final PM action, a replacement is put into place, making the system like new again. Based on Monte Carlo simulation, the ideal PM schedule is determined by minimizing the cumulative cost rate across the system's life cycle, which includes the reliability threshold R, the number of PM cycles N, and the PM intervals Ti (Zhou, 2008).

2.9 Optimization Maintenance

In any industry, maintenance expenses make up a sizable portion of total costs. Any efforts made to achieve optimization in this regard resulted in significant financial savings. Each organization have different approach to the issue of maintenance optimization. The entire life cycle of the equipment must be taken into consideration for this purpose. Prevention of maintenance is a goal in the conceptual stage. Correct "trade-offs" between reliability and maintainability, as well as the incorporation of the maximum amount of redundancy, consequently lower maintenance costs for the desired degree of equipment stability. Standardization of machinery, buildings, and maintenance supplies by itself provides more room for optimization. According to Ravichandran and Mahindrakar (2010), a healthy balance between breakdown and preventative maintenance during the "in service life" and consistently effective training of staff members help to minimize maintenance costs.

Only considering particle size, treatment FR3P3 produced superior outcomes. Out of 9 treatments, FR2-P3 performed the best when sensory evaluation and particle size were taken into account. The TF: TR ratio and overall colour of the tea liquor were unaffected by the feeding rate of the conventional roller, or the pressure used. If the proposed FR3-P3 is used (Abhram *et al.*, 2019), the rolling operation time might be decreased by 30 hours per month.

Mathews and Mathew (2015), in their analysis of failure mode and selection of maintenance strategy for vital machines in a tea industry, claimed that maintenance strategies are chosen for vital machines with higher Risk Priority Numbers (RPN) using an integrated approach of the analytical hierarchy process and VIKOR. CTC units and fermentation units are good candidates for preventive maintenance, while rotor-vanes are good candidates for condition-based maintenance. Monte Carlo simulation is used to simulate the preventive maintenance interval. Production is lost when a machine is down, and money is lost. Currently, the organization employs a corrective maintenance plan. Corrective maintenance approach is obviously inappropriate for critical machinery in the tea sector after reviewing the outcomes of the maintenance strategy selection utilizing AHP and VIKOR. By putting the recommended maintenance procedures into practice, the company will be able to meet demand because equipment downtime will be reduced.

The plant layout that was created reduced the distances that the operators had to travel while doing their duties (Masiyazi *et al*., 2014). The overall distance covered in the workshop decreased 80.3% on average. As a result, the monthly cost of travel and material handling dropped by 99%.

The company lost Ksh. 973,000 a month as a result of frequent mould changes due to improper batching practices. Mould modifications made on average once every seven days (using the EBQ values) based on the economic batch quantities and defined standard periods. It was discovered that mounting and demounting the mould took 40 minutes. The entire cost of altering the mould was decreased to Ksh. 434,000 every month. The goal of maintenance was to improve the plan's overall equipment effectiveness (OEE).

For the planned production system and the existing production system, respectively, two simulation models were created. The simulation models combined all relevant data into a single model, including the MTTR (mean time between failures), planned maintenance, setup times, economic batch amounts, standard times, and computerized manufacturing support system. During the simulation process, the simulation model made advantage of each of these effects. For the best outcomes, the simulation model was run for a duration of one year (Masiyazi *et al*., 2014).

2.10 Model Formulation and Optimization

Every time the system reliability surpasses the reliability threshold R, PM is run in this model. This means that the system reliability at each PM time should be equal to R. Then a reliability equation can be constructed as

$$\boldsymbol{exp}\left[-\int_{\mathbf{0}}^{\boldsymbol{T_1}} \boldsymbol{h_{1(t)}}\,\mathrm{dt}\right] = \boldsymbol{exp}\left[-\int_{\mathbf{0}}^{\boldsymbol{T_2}} \boldsymbol{h_{2(t)}}\,\boldsymbol{dt}\right] = \cdots = \boldsymbol{exp}\left[-\int_{\mathbf{0}}^{\boldsymbol{T_1}} \boldsymbol{h_{2(t)}}\,\boldsymbol{dt}\right] = \boldsymbol{R} \ldots\ldots 5$$

Where: $h_1(t)=b_1b_2.....b_1b_2$ $(\boldsymbol{t} + \boldsymbol{a_1T_1} \ \ + \boldsymbol{a_1T_1} \ \ + \boldsymbol{a_2T_2} \ \ + \boldsymbol{a_{1-1}}), \boldsymbol{t} \in (-\mathbf{0}, \boldsymbol{T})$ 6

From Equation (3), it can be obtained... 7

$$\int_{\mathbf{0}}^{\mathbf{T_1}} \mathbf{h_{1(t)}}\,\mathbf{dt} = \int_{\mathbf{0}}^{\mathbf{T_2}} \mathbf{h_{2(t)}}\,\mathbf{dt} = \cdots \ldots . \int_{\mathbf{0}}^{\mathbf{T_1}} \mathbf{h_{1(t)}}\,\mathbf{dt} = \mathbf{InR} \ldots\ldots\ldots\ldots\ldots\ldots 8$$

The analysis suggests that the likelihood of a system failure during each maintenance cycle is the same. Additionally, it shows that at any given time, the likelihood of an unplanned PM action is the same as the likelihood of a scheduled PM action.

2.11 Optimization of Maintenance Performance for Offshore Production Facilities

Abraha (2011) showed that software tools (such as fuzzy logic, neural networks, and simulation-based optimization) have been developed to manage such complex assets in parallel with the development of new advanced and complex offshore production facilities. They are the micro-sensors, efficient signalling, and communication technologies for collecting data efficiently. However, increasing complexity leads to more difficult and time-consuming diagnostic processes for locating performance-reducing events or forensic processes for identifying failure reasons. There are growing worries that growing complexity, ill-defined interfaces, and unplanned occurrences might quickly result in substantial performance failures and significant hazards. The concern arose given the nature and scope of continuous developments on complexity. Possible ways to resolve include optimizing the functionality, reliability, and security of crucial equipment for it to detect the effects of faulty parts on other system components due to the intricate interdependencies. Nearly 100% availability, or full asset utilization (uptime/ (uptime + downtime)) Risk, cost, and benefit analysis in finance (ROI). Cost, risk level, and the advantages of risk control are all interrelated and therefore cannot be examined independently. The ideal preventative maintenance time interval should be the major research subject to tackle such problems. Too little preventive maintenance would result in wasteful costs, while insufficient preventive maintenance would result in breakdowns, which could negatively affect output and result in financial losses for the company, as was previously described.

It's crucial to optimize maintenance tactics for such a complicated operational environment. By increasing the time between scheduled maintenance visits based on the equipment's actual condition and preventing the recurrence of the seven root causes of failures, it is possible to maximize asset performance, extend effective operating time, reduce repair costs, and minimize the effects of unplanned downtime. Real-time (or near real-time) data combined with operational and environmental parameters are used to determine the actual mean time to failures (MTTF) or loss of functionality (partial/full) of crucial components. Understanding failure, catastrophic failure, incipient failure, and the underlying root causes will be possible with the help of RCM analysis, FMECA, Fail Tree Analysis (FTA), Risk Based Inspection (RBI) and Root Cause Analysis (RCFA) among other tools. Relevant data indicators and instrumentation design are essential for this analysis. Algorithms can be created from data to create equipment profiles, define normalcy, interpret situations of interest, and provide a general picture of the health or status of the important equipment, allowing failures to be avoided or forewarned of beforehand (detection of potential failures).

Optimization of the maintenance process through usage preventive maintenance can further improve the production system and impact positively on economic value of the company (He *et al.*, 2017). The present study sough to determine whether or not the cost of tea production is reduced significantly by usage-based preventive maintenance system. As such, it sought to demonstrate how usage-based maintenance can be of value if implemented in the tea factory under study. The outstanding contribution of this study includes increasing tea production through reduced equipment downtime, reducing repair and maintenance costs, increasing profit margins of the company through less downtime of equipment, and extending useful lifetime of the CTC (crush, tear, curl) rollers. These outcomes have been reported in a previous study conducted in Chebut Tea Factory under the Kenya Tea Development Agency Factory (KTDA) by Kiprotich and Kipsang (2021) on how to minimize tea production costs through usage-based preventive maintenance.

Parida outlines key variables in maintenance management including failure/breakdown frequencies, mean time to repair (MTTR), accessibility, mean time to failure (MTTF), production rate index. Resources such as contractors, labour, materials, equipment and tools are necessary when measuring maintenance management. The Tea Board of Kenya (2005) report indicates that most of its machineries are mainly imported from South Africa, UK, and India, and accounts for 50 % of the capital budget.

2.12 Cost of Maintenance

In establishing maintenance costs and making appropriate decisions, the following features should be considered: Annual maintenance costs expressed as a percentage of replacement value of the assets, asset life in years, current replacement value of the claim, and weighted average cost of capital expressed as a percentage; the year of maintenance opportunity costs as calculated using a weighted average cost of capital free of inflation; and a 20 year-maintenance opportunity cost added up at the average cost of capital rate, along with the capital's present value (Ojukwu, 2006).

The role of maintenance inside the company has undergone a significant transformation over this time. Maintenance was first thought of as failures that needed to be repaired, but today it is a crucial strategic component for achieving company goals (Pintelon & ParodiHerz, 2008). Simes, Gomes and Yasin (2011) emphasize that there is still a need for more research on the subject of maintenance management and performance despite the popularity of numerous themes linked to maintenance. Similarly, Smith (2002) asserts that there is no clear maintenance practice definition in existing literature, leaving readers confused about maintenance practice, action and task distinctions.

Maintenance performance measurements has been discussed extensively by many authors to understand its importance (Visser & Pretorious, 2003; Weber & Thomas, 2006). It is the responsibility of the maintenance managers to assess the performance information so as to observe and govern maintenance outcomes and processes and propose new improvement approaches. Performance measurement is fundamental in building actions needed in pursuit of equipment performance as defined in the strategic goals. The managers are therefore tasked with the responsibility of measuring maintenance process efficiency and effectiveness, determining the association between maintenance input and output parameters, and justifying the need for maintenance investment (Parida & Chattopadhyay, 2007). They argue that downtime duration, production processes, equipment and people affect asset reliability. For economic purposes, assets should be able to return capital for acquiring and maintaining them. When a machine malfunctions, repairs are a preventative action. The management must responsibly prepare for maintenance by making sure spare parts are in stock, whether it is required on a regular basis or is discovered during an inspection.

In line with the above sentiments, it is apparent that tea factories should develop and execute effective maintenance tasks to ensure equipment reliability and ensure the root-cause analysis is done and action closed. This can be ensured by optimizing reliability and performance preventative maintenance, autonomous maintenance, innovation and technology for safe working practices. Black tea processing involves high operating costs. In addition, as an evolving process, it requires a lot of overhauls in the production processes to integrate new technologies that can improve the production. Many of the tea factories in Kenya have not embraced new technologies fully. As such, their operation systems are becoming increasingly obsolete. According to Lewis (2004), “Numerous new technologies are not fully understood, operating systems are becoming more complex, and operational reliability is far lower than anticipated”.

Studies on preventive maintenance have used different approaches to evaluate outcomes. For instance, Gilardoni *et al*. (2016) used numerical algorithms and mathematical models while Mabrouk *et al.* (2016) adopted a Monte Carlo for simulation. Nourelfath *et al*. (2016) examined preventive maintenance timing relative to quality and cost using Markov method.

2.13 Components of Tea Processing Plant

In Kenya, tea is grown in high-altitude regions located 1800 to 2700 meters above sea level, with an annual rainfall of 1800 to 2500 mm. Although the tea-growing regions are dispersed over the nation, they are primarily located to the west and east of the Great Rift Valley (Hilton, 1973; Owuor *et al.*, 2008). Small and big estate sub-sectors are the two main divisions of the market. Average holding sizes for big estates ranges from less than one hectare to twenty hectares. Small size sub-sector account for approximately 62 percent of the overall production and 66 percent of the total area under tea crop (Anon, 2002, 2006).

Tea processing involves weathering, cutting, tearing and curling (CTC), fermentation, drying, sorting, packing and dispatch units. This processing takes about 10 to 12 hours from time of receiving to packing. In each section, there are combination of process equipment ranging from material handling, rotor vanes, rollers, blowers, dries, vibrators boiler and its accessories and storage bins. Processing starts with leave withering and then maceration by rotor vanes. This is followed by cutting of the tea leaves using CTC machines comprising of rollers rotating in opposite direction at varying speeds. After that, the resulting tea leaves are fermented in the continuous fermentation unit (CFU). Finally, they are fed into driers to minimize moisture content to standard limits. Like all the other 66 tea factories managed by KTDA energy is a key production input making up about 20% of the total cost of tea processing. The other costs come from labour, maintenance, transport among others (Maina, 2018).

In order to improve the relationship between operating profits and equipment ownership, it is necessary to develop optimal strategies for processing tea. These strategies should balance the cost of equipment failure and the annual cost of maintenance, the associated production losses and the initial cost of the equipment. With excellent optimization, maximum equipment reliability, prolonged equipment life and general delivery of cost-effective reliability are realized (Bukar & Tan, 2019).

All manufacturing and production facilities incur significant operational expenses that are mostly related to maintenance. Maintenance expenses range from 15 percent to 40 percent of the costs of producing goods, depending on industry (Mondal *et al.*, 2016). The sort of maintenance techniques used affects how well machines perform. Industry-used machines require regular maintenance because machine failures could lead to a loss in production (Shafiee & Srensen, 2019). Inappropriate maintenance practices can raise the cost of maintenance, which will therefore raise the cost of production.

According to BSI (1984) and Pintelon and VanPuyvelde (2006), maintenance constitutes all technical, management, and administrative actions taken throughout the course of an item's lifecycle with the goal of keeping it in or restoring it to a state where it can perform the needed function. Kelly (2006) highlighted that a maintenance strategy entails the selection, creation, or customization of several decisions regarding repairs, replacements, and inspections. In collaboration with production and other relevant tasks, it is concerned with creating the best life plan for each manufacturing unit and the best maintenance schedule for the entire plant. Maintenance strategy designates the events such as time, failures, conditions, triggers and types of maintenance (repair or replacement). Access to credit and extension services, ratio of factory running capacity to full capacity, and main grade percentage determines small-holder farming efficiency (Abate, Dessie & Mekie, 2019). This suggests that availing credit and extension facilities to tea factories could help increase their profit efficiency.

2.14 Cost of Tea Factory Operations

Globally, tea prices have fallen consistently since 1998, but cost of production has risen. The rise in fuel and electricity charges, wage awards and transport costs have rendered the sale of tea produce considerably unsustainable (Melican, 2004). Kenya is third among the world’s largest tea producers after China and India and the largest in Africa. The tea industry provides direct employment to close to a million Kenyans. It is the country's leading export earning more than Ksh.100 billion in 2014, directly employing 120,000 workers in addition to 650 smallholders who grow tea (Ogage, 2015). Nevertheless, in Kenya, increase in the cost of production has become a predominant challenge facing the tea industry (Tata Global Beverages, 2002). With the high cost of production and operation cost, tea farming is slowly being side-lined in Kenya as prices can barely cover the cost of production. In 2000, the World Bank predicted an 11 percent tea decline monetary terms.

According to Maina (2018), in research on enabling environment for Kenyan tea sector, investment in new methods has been very slow and many factories are experiencing declining qualities as a result of out-dated and worn-out factory equipment. Such equipment decline is a symptom of resistance to automation practices.

One way the Kenya government has attempted to address the rising cost of tea production is considering granting all tea factories Export Processing Zone (EPZ) status to guarantee constant electrical power supply as well as lower tariffs (Gesimba *et al.*, 2005). This is based on the fact that power is a major challenge in tea processing. Therefore, the Kenya government constantly seeks ways to optimize tea production by examining strategies to save on costs of production and to mitigate emerging challenges (Terer & Kipkorir, 2019). Kenya's tea industry thus requires immediate and comprehensive productivity enhancement programmes to enable it to survive in the long-term. The point of interest of this study was to assess how productivity in Kenya's tea sector may be enhanced through optimization of production variables.

The cost of tea production is clustered under five areas, namely green leaf cost, processing cost, heat energy cost, electric energy cost and overheads. According to Asian Institute of Technology, energy for processing of green leaf into graded black tea should take at most 17 percent of the total production cost, and 40% of the cost should go into factory labour, machinery maintenance, packaging materials and factory sundries. To control the performance of industrial plant to some standards, it is advisable to carry out maintenance management (Parida, 2006). Maintenance management requires one to plan, schedule, organize and control maintenance activities appropriately. It revolves around maintenance effectiveness and the results after maintenance with a desire to minimize maintenance costs and improve production reliability, quality, and cost.

Breakdown maintenance has always been considered as being unprofitable because it directly reduces production. However, it is good to note that both preventive and breakdown maintenance result in reduced availability of equipment (Poór, Ženíšek & Basl, 2019). Too much of preventive maintenance may result in high number of equipment downtime and subsequent loss of production. To control the preventive maintenance programme's extent, the cost aspect of the of the programme in comparison to the measured reduction in total repair cost, comparative improvement of equipment availability as well as the present utilization of equipment will be taken into consideration (He *et al.*, 2017). The justification is weak if the cost of preparing for a preventative maintenance inspection is equal to the cost of repairs following a failure followed by inspection. Contrarily, preventive maintenance inspection should be taken into consideration if the malfunction could lead to serious damage to the equipment and a more expensive repair (Poór *et al*., 2019). The cost of breakdown repair will be high and that of preventative maintenance will be minimal if there is less preventive maintenance. Preventive maintenance costs gradually rise along with it in the initial stages and later quickly. However, when preventive maintenance increases, breakdown cost declines gradually after initially falling substantially. Thus, an ideal degree for both preventative and breakdown maintenance can be chosen.

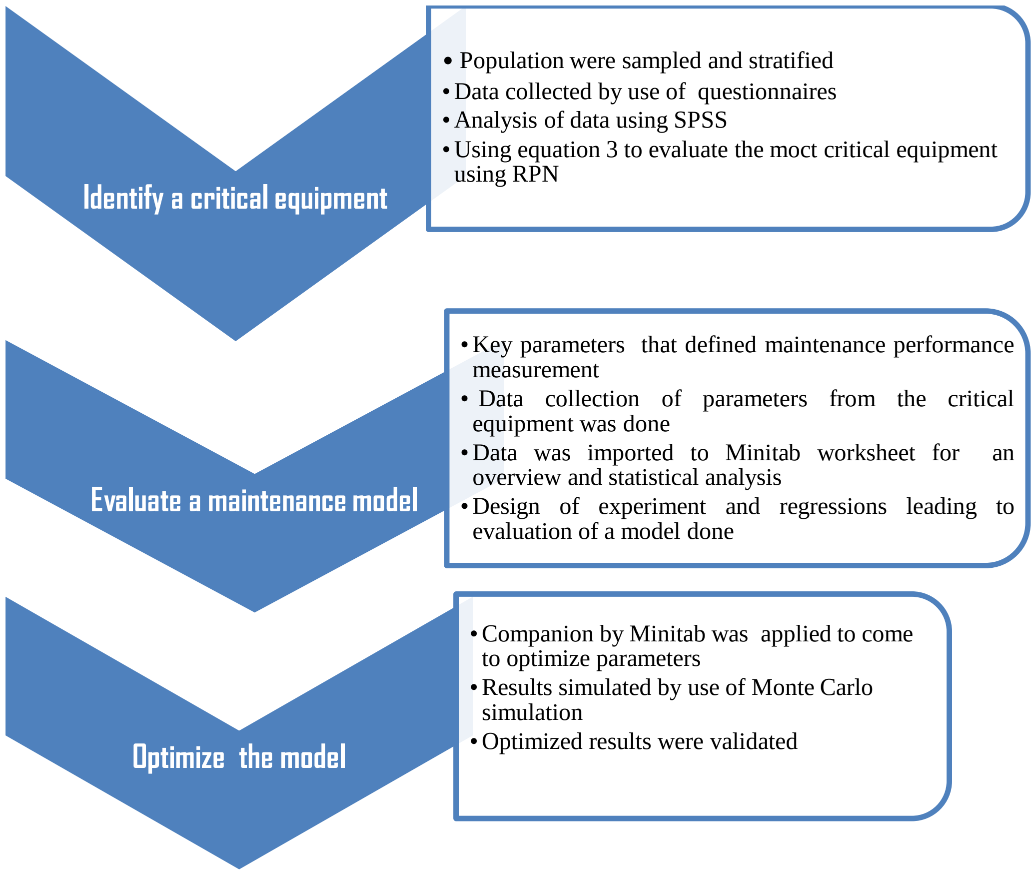
CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the research design, the population, and sampling methods were highlighted. The method further gave description of data collection and data analysis used. Efforts to achieve optimization was aimed at yielding substantial savings so attention had to be paid in the total life cycle of the equipment. The balance between Reliability, Availability and maintainability as well as building in optimum redundancy resulted in reduction of maintenance costs for the desired level of equipment stability. Standardization of equipment, plant and maintenance stores itself offered an additional scope for optimization.

3.2 Conceptual Framework



3.3 Research Design

The objective of this research was to carry out an optimization of maintenance of critical machine in tea processing as a case study of Litein Tea Factory. Data on the processed tea, breakdowns and prescribed maintenance were key in the focus that eventually enabled the research to achieve the overall objective through identification of the critical machine. The data within the equipment were then collected for analysis and study of the interrelations of variables. Procedural development of a model formulae as guided by availability, reliability and the maintainability of the established critical equipment was done, and the developed model subsequently optimized for effective and efficient application. The research methodologies were mainly inductive applied research designed to investigate all states of productivity and processes and procedures within Litein Tea Factory. General conclusions were made as derivatives of the findings and at some point, the deductive approach.

3.4 Research Population

The research focused on the equipment within Litein Tea Factory. The population characteristics were clearly identified, and Random stratified sampling method employed in data collection within the processing plant. Total of 22 relevant personnel was identified as resourceful to respond to the questionnaires. The positions were chosen mainly because they were considered as the main users of the relevant machines and custodians of needed resource documents. Target populations were stratified based on department as follows:

- Management and administration -4
- Production workers -6
- Maintenance and repair-6
- Quality control and inspectors-2

- Warehouse and logistics-2

Since the target population in each Stratum was small constituting a total number of 22, every member stood 100% chances of being interviewed so as to come up with a sample size of 22 and achieve highest level of precision possible.

3.5 Data Collection Methods

Both primary and secondary data were collected, coded, and analysed using Statistical Package for the Social Sciences (SPSS) and Minitab 17. Highly reliable methods to deliver valid results will be used. These include Modelling and Simulation, Analysis of Variance (ANOVA), Pareto analysis, Root Cause analysis, Statistical analysis, Time study, Experimentation, and interviews. All data and results obtained were summarized and presented in forms of tables and figures.

Maintenance intervals for the subsequent years were simulated using Monte Carlo Simulation. Monte Carlo was chosen over any other software due to its ability to model and validate uncertainty and variability in complex system Time between failures of all machines and frequency of occurrence of each time between failures were also collected from the previous year records and their probability of occurrence calculated using binomial distribution. The cumulative probabilities were found out and broken down into random number range and preventive maintenance interval simulated for the next year. The simulated maintenance intervals were concurrently generated. The findings obtained were discussed in order to make it useful in making inferences and recommendations about machine efficiencies, monitory losses and possible ways to remediate on downtimes and ultimate optimization of production parameters.

3.6 Critical Equipment in Tea Processing

Failure of the component was the main reason for the machine to breakdown. This Parameter was seen to have effects on machine downtime, Failure type, Service time, Number of breakdowns and operating time. Throughputs mostly as the input was also considered as a component greatly affected by the same independent variables. The failure mechanism was considered in the analysis of identifying possible external variables bringing about the failure component. Any machine considered to significantly impair the ability to safely meeting business were deemed critical. Therefore, highest criticality levels were the point in time when measures of production were zero. From the key production units in the factories processing plant, data were collected, and analysis were done in order to evaluate a unit or an equipment that was most critical in the processing of black tea based on empirical value of criticality index.

The Data that was required for achieving critical equipment was collected with the help of questionnaire from maintenance team, machine operators and the shift in charge (see Appendix 1 for questionnaire used to collect data). With the collected data, table of failure mode and effect analysis was dully filled entering the following data:

- Part/design parameter chosen for assessment potential.
- Failure mode which are the ways that the design parameter can fail to meet the requirements.
- Potential failure effects which is the output results of each failure mode where a failure mode may have multiple failure effects.

- Severity rating (SEV). The severity of failure effect using a scale of 1 to 10 scale where 10 is the high severity index and 1 respectively low.
- Potential causes brought about the failure mode.
- Occurrence rating (OCC), which entails the how frequently the cause is likely to occur again with the scale of, from 1 to 10 where 10 is the highest and 1 the lowest, respectively.
- Current control indicating how the failure mode or cause is detected or controlled.
- Detection rating (DET) being the ability of each control to detect or control the failure cause or mode with the scale of 1 to 10 where 10 is poor detection or control whereas 1 is the highest detection or control which detects before real failure.
- Using Equation 3, the Risk Priority Number (RPN) which is the product of SEV, OCC and DET scores is evaluated.
- The highest RPN indicates a more score, more frequent or less controlled problem.

3.7 Establishing a Mathematical Model for a Critical Equipment

To evaluate a mathematical model for critical equipment in tea processing plant, the key parameters that defined maintenance performance measurement namely downtime, throughput, operating time, number of failures, failure type and service time was outlined.

- Data collection of parameters from the critical equipment identified being CTC was carried out for 33 working days and recorded in an excel worksheet.
- The collected data was then imported to Minitab worksheet for an overview.

- Design of the experiment using statistic approach was carried out by choosing factorial design with 2-level factorial, 6 factors and 28 runs as displayed in the available designs. The design could have required 64 runs but with the constrain of 28 runs, fractional factorial design is used (see Table 3)
- Open Minitab and go to the start menu.
- Select Design of Experiment (DOE) and the "Factorial"
- Choose" Factorial design" and set the number to be 6.
- The number of levels is specified as 2.
- Set the number of runs to be 28.
- The factorial design is then generated by clicking "Ok."
- Descriptive statistics for the key variables was generated.
- Suitable statistical model within Minitab was selected.
- Regression analysis for the parameters was carried out and the necessary uncoded model imported.
- Coefficients for each parameter were generated.
- The respective coefficients in the generated regressions were replaced in order to come up with the desired coded regression models.

Table 3: Created Factorial Design Available in the Minitab

Available Factorial Designs (with Resolution)

	Factors													
Run	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
4	Full	III												
8		Full	IV	III	III	III								
16			Full	V	IV	IV	IV	III	III	III	III	III	III	III
32				Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
64					Full	VII	V	IV	IV	IV	IV	IV	IV	IV
128						Full	VIII	VI	V	V	IV	IV	IV	IV

Available Resolution III Plackett-Burman Designs

Factors	Runs	Factors	Runs	Factors	Runs
2-7	12,20,24,28,...,48	20-23	24,28,32,36,...,48	36-39	40,44,48
8-11	12,20,24,28,...,48	24-27	28,32,36,40,44,48	40-43	44,48
12-15	20,24,28,36,...,48	28-31	32,36,40,44,48	44-47	48
16-19	20,24,28,32,...,48	32-35	36,40,44,48		

According to Table 3, Factorial design is then analysed in order to come up with:

- Needed factorial design.
- Factorial regression

Analysis of variance

- Model summary.
- Model summary.
- Regression equation
- Effects of pareto

3.8 Optimization of Maintenance Parameters in the Critical Equipment

To come up with optimization, Companion by Minitab is applied systematically as:

1. Definition of the model.
2. The generated regression equations for both Number of failures and through put are applied.
3. The correlation between the Y and X parameters are checked.

3.9 Results Simulation

Simulation in the critical equipment processing unit were carried out using Monte Carlo simulation method. The simulated model was integrated in all the pointed variables in each case. The objective was to achieve the predetermine outcome for the new design, therefore the numerical results from other quantitative research methods was used for simulation. The present production system of the company and the intended production system were also simulated. The simulated results acted as a basis for evaluation of the new design described as:

- Distribution of data being examined to ascertain the summary statistics.
- Determination of the data to check on extends at which they could meet the specified requirements.
- Definition of Model assumption.
- The parameters optimization process.

3.10 Validation of Results

The process involved confirmation of the proposed changes in the results of the outlined parameters.

3.10.1 Definition of Metrics

Metrics used to evaluate the effectiveness of the optimization process were clearly defined as:

1. The process performance to ensure they are generally above the accepted minimum of 1.33 an implication that it meets the specification limits with some margin.

2. Values falling outside the specification limits being 0.00% and depicting a process of a normal distribution.
3. Standard deviation to relatively be as small as possible.
4. Root mean square percentage being relatively high as possible.

3.10.2 Baseline Comparison

The performance of parameters obtained after optimization with the baseline parameters collected before the implementation of the optimization process in order to help in evaluating the degree of improvement achieved after the process.

3.10.3 Sensitivity Analysis

Using statistical methods, analysis of data collected during validation phase is carried out. Analysis of variance, regression and Parato analysis were tested to observe the statistical significance of the improvement made.

CHAPTER FOUR

FINDINGS AND DISCUSSION

4.1 Introduction

This chapter gives the relation through analysis of parameters in the collected data in tea processing as collected within Litein Tea Factory in Bureti Sub-County of Kericho County. The chapter first outlines the relevant daily data on the processing units collected for 40 days then cross-validated with the historical data in the previous 2 years. The experimental results in respect to identification of the factory's critical equipment, subsequent optimization, and simulation of the collected results.

4.2 Response Rate

According to Nulty (2008), response rate is defined as the number of respondents who successfully fill the data collection instrument vis-à-vis the total number of respondents to which the instrument was administered. Concerning this study and in line with objective one, according to Table 4 a total of 22 questionnaires representing 100% were issued out of which 19 representing 98.64 was validly filled and submitted back while 3 of them representing 1.36% were filled without following prerequisite instructions thus accounted for as un-received responses. The findings surpassed the recommended threshold of 75% recommended by Nulty (2008). The significantly high response rate was largely attributed to the administration of the questionnaires by the researcher in person who explained to the respondents the rationale of taking part in the study.

Table 4: Response Rate

	Frequency	Percent
Expected responses	22	100.0
Received responses	19	98.64
Un-received responses	3	1.36
Total	**22**	**100.0**

Since the target population in each Stratum was small constituting a total number of 22, every member stood 100% chances of being interviewed so as to come up with a sample size of 22 and achieve highest level of precision possible.

4.3 Respondents Information

The study examined various demographics in respect of technical machine operators and maintenance technicians working with the factory. The demographics examined included level of education and also the period of working. Regarding the level of education, the result of the analysis is as illustrated in Table 5 where 10 respondents representing 52.6% are certificate holders, 6 representing 31.6% hold Diplomas, 2 being 10.5% are Degree holders while 1 representing 5.3% of the total respondents have Post Graduate degree.

The level of education was assessed to ascertain whether the respondent possesses sufficient technical skills due to adequacy or inadequacy of training to understand the questions being asked in line with the objectives. From the analysis, not much variance was noticeable in the responses given with regards to the level of education nor the stratified field of work an indication that the questions was clarified and simplified to be contextualized by the respondents.

The interaction with the respondents prior to filling the questionnaires was positive and was indicated by level of clarity, reduction of misunderstanding, increased engagements and contextual understanding as the researcher made clarity of the objectives.

Table 5: Distribution of Respondents by Level of Education

	Frequency	Percent
Certificate	10	52.6
Diploma	6	31.6
Degree	2	10.5
Postgraduate	1	5.3
Total	**19**	**100.0**

4.3.1 Distribution of Respondents by Experience

Table 6 represents a total of 19 respondents. There were 4 respondents (21.1% of the total) who reported having less than 1 year of experience. There were 7 respondents (36.8% of the total) who reported having 1 to 5 years of experience. 6-10 years: There were 6 respondents (31.6% of the total) who reported having 6 to 10 years of experience. There were 2 respondents (10.5% of the total) who reported having more than 10 years of experience. The cumulative percent column helps us understand the distribution of experience levels. From the cumulative percent column, it was observed that 21.1% of the respondents have less than 1 year of experience, 57.9% have 1-5 years of experience or less, and finally, 89.5% have 6-10 years of experience or less.

Table 6: Experience Level of Respondents

		Frequency	Percent	Cumulative Percent
Valid	Less than 1 year	4	21.1	21.1
	1-5 years	7	36.8	57.9
	6-10 years	6	31.6	89.5
	More than 10 years	2	10.5	100.0
	Total	**19**	**100.0**	

4.4 Severity of Machines in the Processing Unit

Table 7 presents information on the average severity and standard deviation of severity for various processes and associated machine units. Severity values close to 10 indicate higher severity, while values close to 1 represent lower severity. Table 7 provides an overview of the severity levels for different processes and machine units. Higher average severity values, along with larger standard deviations, indicate potentially more severe issues or variations in the respective processing units.

Table 7: Severity of Machines in the Processing Unit

PROCESS	MACHINE	Average severity of the machines in processing unit	Standard deviation of severity of the machines in processing unit
Withering	Conveyor	3.790	2.043
	Fans	2.105	0.737
	Leaf sifting	3.368	1.116
Leaf maceration	Shredder	4.789	1.358
	Rotor vane	5.316	1.416
	PVC conveyor	4.526	1.348
Cutting Tear Curl (CTC)	Axial pitch adjustment	5.947	1.615
	Cage unit	5.842	0.898
	Crusher	6.053	1.311
	Rollers	7.211	2.507
Continuous fermentation	Oxidation chamber	3.316	1.293
	Ball breaker	3.947	1.545
Convectional drying	Floats	4.526	0.905
	Pre-drying	4.000	1.374
	Tray circuit	4.474	1.467
	Strainers	4.316	1.293
Sorting	Pre-sorter screens	3.895	1.524
	Vibro-screens	3.684	1.057
Packing	Bucket Elevator	2.526	1.219
	Packing hopper	2.737	1.098
	Chains and sprockets	3.211	1.182

In withering processing units: The average severity of the conveyor was 3.790, with a standard deviation of 2.043. Fans had average severity of 2.105, with a standard deviation of 0.737 indicating less severe. Leaf sifting was 3.368 severe, with a standard deviation of 1.116. Leaf maceration: The average severity of the shredder: processing unit was 4.789, Rotor vane was more sever compared to shredder 5.316, with a standard deviation of 1.416. PVC conveyor had a mean severity of 4.526. Cutting Tear Curl (CTC): Axial pitch adjustment: The average severity of the processing unit was rated 5.947, with a standard deviation of 1.615. Cage unit, Crusher, Rollers were highly rated compared to the machines at 5.842, 6.053 and 7.211 respective average severity of the processing unit. Continuous fermentation: The average severity of the Oxidation chamber was 3.316, with a standard deviation of 1.293 and Ball breaker was 3.947. This occurrence implies the machines were less severe.

In convectional drying: Floats, pre-drying, tray circuits and strainers all averaged to have at least 4-point ratings in severity with their respective small standard deviations. On the sorting processing units: Pre-sorter screens: The average severity of the processing unit was 3.895, with a standard deviation of 1.524.

In vibro-screens: The average severity of the processing unit is 3.684, with a standard deviation of 1.057. On packing processing units: bucket elevator, packing hopper and chains and sprockets were less severe according to their ratings.

4.5 Frequency of Failure Mode

The provided Table 8 presents average ratings for various factors related to processing units in different categories. The factors include loose tension, breakdown, crushing, wear and tear, breakage, and bluntness. They were rated in a scale of 1 to 10, where 10 is the highest and 1 being the lowest.

It indicates the failure modes likely to occur in the corresponding process unit. On withering section, the average rating for loose tension was 4.844. The average rating for breakdown in the withering processing unit was 4.053. The ratings on crushing, wear and tear, breakage, and bluntness were averaged below 4 out of 10. This cluster of failure mode in machines comparatively appear to exhibit weightier failure characteristics than the rest. The average rating for loose tension in the maceration processing unit was 4.842. Bluntness was rated at 2.789 implying less likely to fail.

Some of the sections less likely to fail were CFU (rated less than 4). The average failure modes in drier section were around 4. This also implies critical section since machines tend to fail.

Table 8: Frequency of Failure Mode

Processing Unit	Loose tension (average rating)	Breakdown (average rating)	Crushing (average rating)	Wear and Tear (average rating)	Breakage (average rating)	Bluntness (average rating)
Withering	4.844	4.053	4.368	3.421	3.158	3.842
Maceration	4.842	3.842	4.316	3.263	3.737	2.789
CTC	5.053	5.263	4.526	4.842	4.842	3.842
CFU	3.053	3.842	3.842	3.895	4.000	3.105
Drier	3.842	4.526	3.947	4.316	3.895	3.737
Sorting	5.526	4.526	4.263	4.211	4.474	3.263
Packing	4.421	4.263	3.895	3.947	4.421	4.105

Table 9: Analysis of Failure Mode

Processing Unit	Loose tension (average rating)	Breakdown (average rating)	Crushing (average rating)	Wear and Tear (average rating)	Breakage (average rating)	Bluntness (average rating)
Withering	High	Low	Higher	Lower	Lowest	Higher
Processing Unit	Loose tension (average rating)	Breakdown (average rating)	Crushing (average rating)	Wear and Tear (average rating)	Breakage (average rating)	Bluntness (average rating)
Maceration	Medium	Lower	High	Lowest	Lower	Lowest
CTC	Higher	Severe	Severe	Severe	Severe	Severe
CFU	Lowest	Lower	Lowest	Low	Medium	Lower
Drier	Lower	High	Low	Higher	Low	Higher
Sorting	Severe	High	Medium	High	Higher	High
Packing	Low	Higher	Lower	Medium	High	Severe

In the analysis of failure modes, any process unit with comparatively low index each cluster was considered lowest and that with comparatively high index was respectively considered severe. The subsequent indices were considered lower, low, medium, high and higher in that order (see Table 9).

4.5.1 Detection Control

According to Table 10, the average detection abilities of different control mechanisms in detecting failure modes within various processing units are illustrated. The scale ranges from 1 to 10, where 10 indicate poor detection ability and 1 represents the highest detection ability. Lower average detection ratings indicate a higher ability to detect failure modes, while higher ratings represent a poorer ability to detect failure modes. From the Withering section: Programmable Logic Control had an average detection ability of 2.263.

The average detection ability of control meters in the withering processing unit was 6.052. The average detection ability of thermal mass flow meters in the withering processing unit was 4.684.

For the alarms in the withering processing unit, it was 1.842. The process shows that alarm and Programmable Logic Control had the highest detection abilities compared to control meters and thermal mass flow meters. Overall, in the maceration, CTC, CFU, Drier and Sorting; Average detection ability of the Programmable Logic Control and Alarms had the highest detection abilities respectively. Whereas Control Meters and thermal Mass Flow Meters also had poorly detection abilities.

Table 10: Detection Control

Processing unit	Programmable Logic control (Average detection)	Control meters (Average detection)	Thermal mass flow meters (Average detection)	Alarms (Average detection)
Withering	2.263	6.052	4.684	1.842
Maceration	2.211	6.000	4.526	1.842
CTC	2.211	3.579	4.210	1.842
CFU	2.526	4.368	4.053	1.947
Drier	2.316	4.526	3.684	1.895
Sorting	2.263	6.737	5.105	2.000

4.6 Determining a Critical Equipment in Tea Processing Plant

According to Table 11, critical equipment was identified, through failure mode effect analysis by application of Minitab. The process computes the respective criticality of varies parts using General failure mode, potential failure effects, severity rating, detection rating, occurrence rating and current controls. Other parameters are RPN which is the product of Severity, Occurrence rating and detection rating. The RPN then recommended action to be carried out on the production unit which was to generate a model and optimize the most critical production unit.

Table 11: Failure Mode Effect Analysis of the Tea Processing Unit

Parameter	**Potential failure modes**	**Potential failure effects**	**SEV**	**Potential cause**	**OCC**	**Current controls**	**DET**	**RPN**	**Action recommended**
Withering	Conveyor looseness	Slowing down production	3	Drop in machine efficiency and effectiveness	3	Alarms Control meters Thermal meter	7	63	3th Critical
	Motor breakdown								
	Crushing in leaf sifting Crushing in leaf sifting								
Maceration	Shredder crushing	Downtime	5	Drop in availability efficiency and effectiveness	4	Alarms Control meters	7	140	2th most critical
	Rotor vane breakage								
	Wearing out of conveyor								
CTC	Failure in axial pitch	Downtime	7	Drop in availability efficiency and effectiveness	6	Alarms Control meters	6	252	The most critical unit Recommended for optimization
	Crushing in cage unit								
	Wearing off in belts								
	Breakage in air ducts			effectiveness		flow meters			
	Wearing out of belt								
Drier	Pre-drier breakage	Drop in production	2	Drop in availability efficiency and effectiveness	2	Alarms Control meters Thermal flow meters	8	32	5th critical
	Jamming in trays								
	Steam line blockages								
	Failure in accessories								
Sorting	Pre-sorter breakdown	Drop in production	2	Reduction in efficiency and effectiveness	1	Alarms Control meters	7	14	6th criticality
	Vibrascreen breakdown								

According to Table 11, application of failure mode effect analysis in evaluating machine criticality established CTC with an RPN index of 242 as the most critical unit in tea processing and therefore identified for its production parameters for modelling and optimization.

4.7 Optimization of Maintenance

Fit model for each variable and responses was checked before doing it for the multiple responses. Through put and Number of failures was identified as dependent variables (Y). Whereas downtime, operating time, service time and failure type as independent variables(X). By use of optimization plot, variables settings were adjusted in order to establish how the set changes affect the responses. The interrelation between X and Y variables generated regression models to be optimized. This process was done purposely to achieve optimized parameters for maintenance measurement.

4.7.1 Probability Plot for Maintenance Parameters

Probability plot for maintenance parameters was done in order to evaluate the fit of parameter distribution as well as to estimate sample distribution in all maintenance parameters and display of each value verses the percentage of values in the sample along fitted distribution line.

4.7.2 Throughput

According to Figure 1, probability plot of throughput was established to be following normal distribution with 95% as the P-value being greater than 0.005 hence visualize fit distribution and display of estimated percentiles.

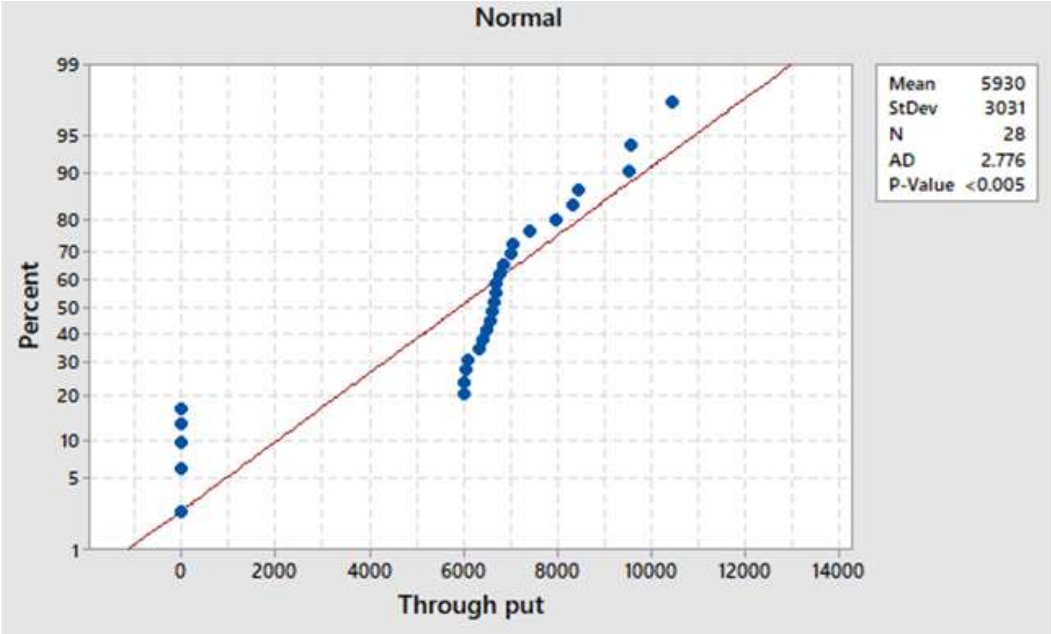


Figure 1 Probability plot for throughput.

Probability plot helps in assessing whether data follows probability distribution, and the plot symbolizes how closely the data points align with the theoretical distribution hence fitting the distribution well.

4.7.3 Number of Failures

According to Figure 2, probability plot of number of failures was established to be following normal distribution with 95% as the P-value being greater than 0.005. Hence visualize fit distribution and display of estimated percentiles.

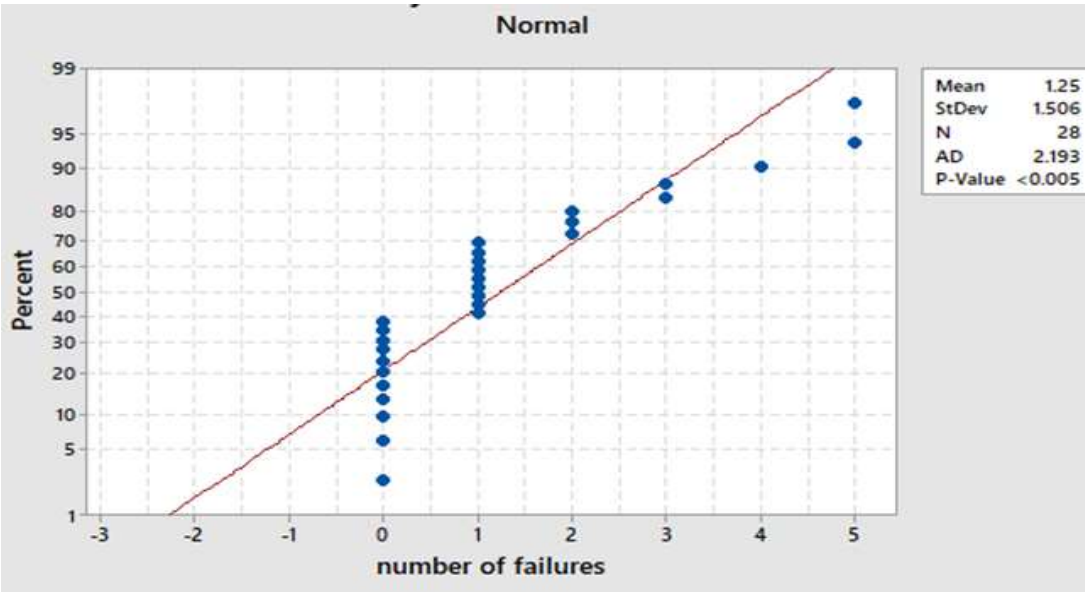


Figure 2 Probability plot for number of failures.

This probability plot symbolizes how closely the data on number of failures align with the theoretical distribution hence fitting the distribution well.

4.7.4 Downtime

Downtime probability plot identified plot line representing normal variations. Values of the variables verses the percentage of values in the sample displayed in Figure 3. Data points relatively close to the fitted normal distribution and a P-value of greater than the significance level of 0.005. This probability plot symbolizes how closely the data on downtime align with the theoretical distribution hence fitting the distribution well.

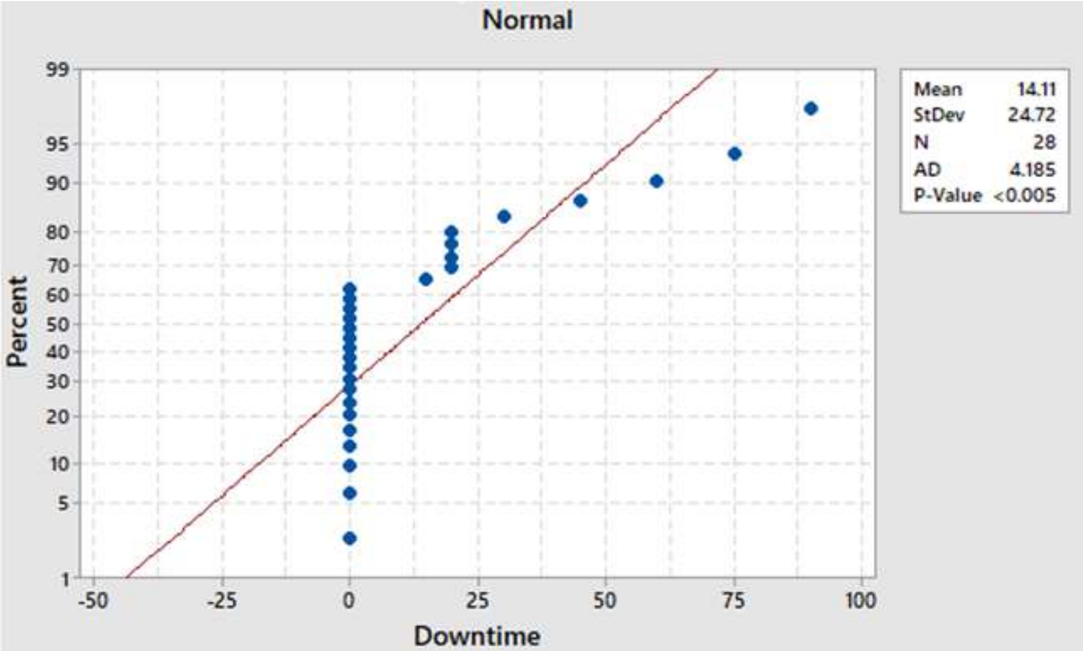


Figure 3 Probability plot for downtime.

4.7.5 Operating Time

Operating time probability plot identified plot line representing normal variations. Values of the variables verses the percentage of values in the sample displayed in Figure 4. Data points relatively close to the fitted normal distribution and a P-value of greater than the significance level of 0.005. This probability plot symbolizes how closely the data on operating time align with the theoretical distribution hence fitting the distribution well.

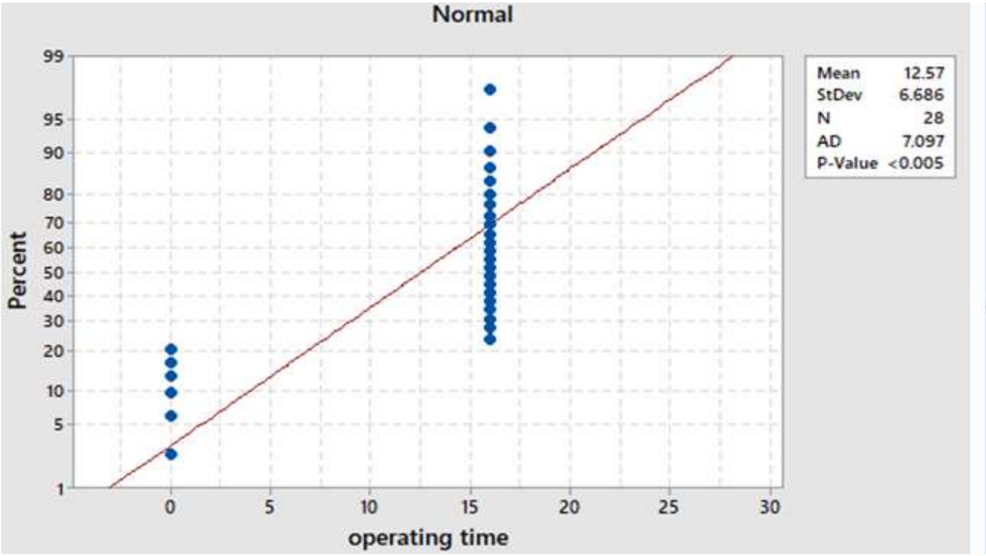


Figure 4 Probability plot for operating time.

4.7.6 Service Time

According to Figure 5, evaluation of fit of a distribution to service time data is displayed together with estimated percentiles and comparison of sample distribution. Each value verses in the percentage of values in the sample that are less or equal to it along fitted distribution line. Data points are relatively closer to the fitted normal distribution line is proved to be normal-95%.

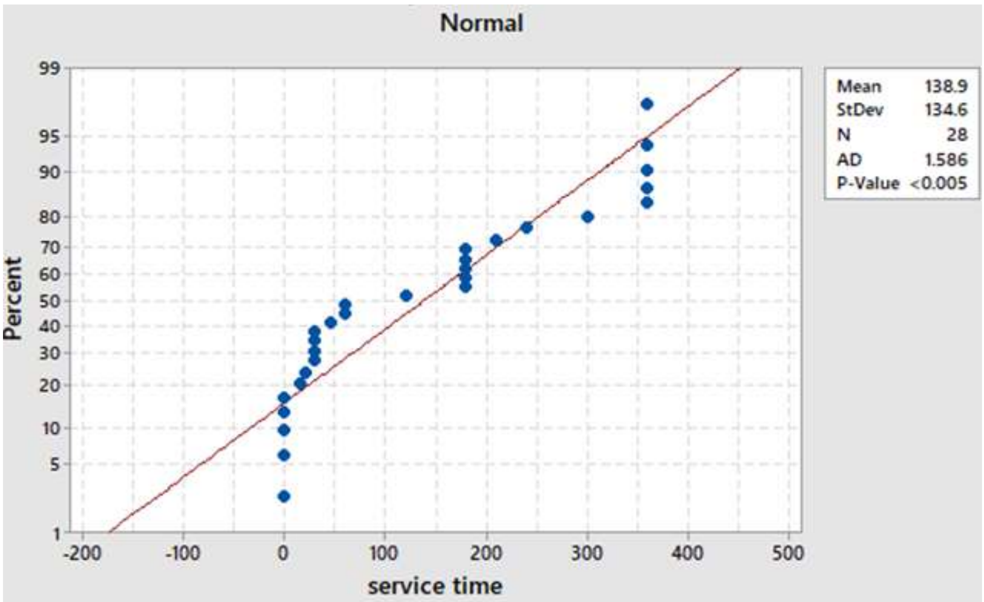


Figure 5 Probability plot for service time.

This probability plot symbolizes how closely the data on service time align with the theoretical distribution hence fitting the distribution well.

4.7.7 Failure Type

Failure type probability plot acknowledged plot line representing normal variations. Values of the variables verses the percentage of values in the sample displayed in Figure 6. Data points relatively close to the fitted normal distribution and a P-value of greater than the significance level of 0.005.

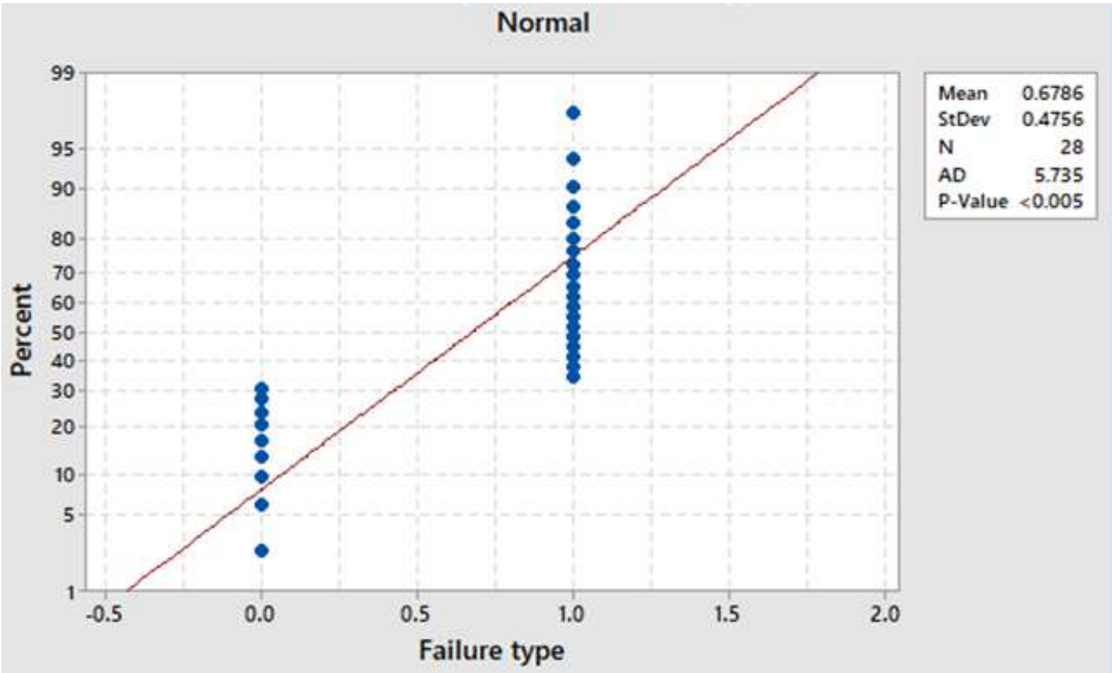


Figure 6 Probability plot for failure type

This probability plot symbolizes how closely the data of failures type align with the theoretical distribution hence fitting the distribution well.

4.8 Modelling of Maintenance Parameters for the Critical Equipment

Relationship between the Y and X variables was described in regression model. Y was considered response variables which are Throughput and Number of Failure while X was considered as constant variable namely, Downtime, Operating Time, Service Time, and Failure type. From the Minitab, the ANOVA results and uncoded regression for Throughput is as shown in Appendix 2. While that of the number of failures is in Appendix 3. Optimal settings for input parameters that can be controlled to achieve defined objective leading to better output in maintenance performances were generated.

4.8.1 Modelling of Throughput

From the uncoded model generated from Minitab workspace, Parameters can be coded by Considering $troughput = y_1$, $downtime = x_1$ $operating\ time = x_2$, $service\ time = x_3$ $Failure\ time = x_4$, (see Appendix 5). The throughput model would therefore be:

y_1 = 9516 + 513x_1 - 643.6x_2 + 30.84x_3 - 2816x_4 4.90x_1x_2 - 2.334x_1x_3 - 460x_1x_4 + 0.668x_2x_3 + 725x_2x_4 - 48.46x_3 x_4 + 2.489x_1 x_2x_4 .... (9)

4.8.2 Effects Pareto for Throughput

According to Figure 7, the importance of the effects of independent variables on the dependant variable y_1 is illustrated on the Pareto chart bars. The absolute value of effects of parameters that cross over the reference line measured as 2.120 on the standardized effect are statistically significant at 0.05 level. It is however difficult to establish its effects hence need for normal probability plot of standardized effects in order to examine the magnitude and the direction of the effects on one plot. The process helps the prioritize efforts by showing which factors have the greatest impact on throughput by allowing fair comparison of the influence of different factors.

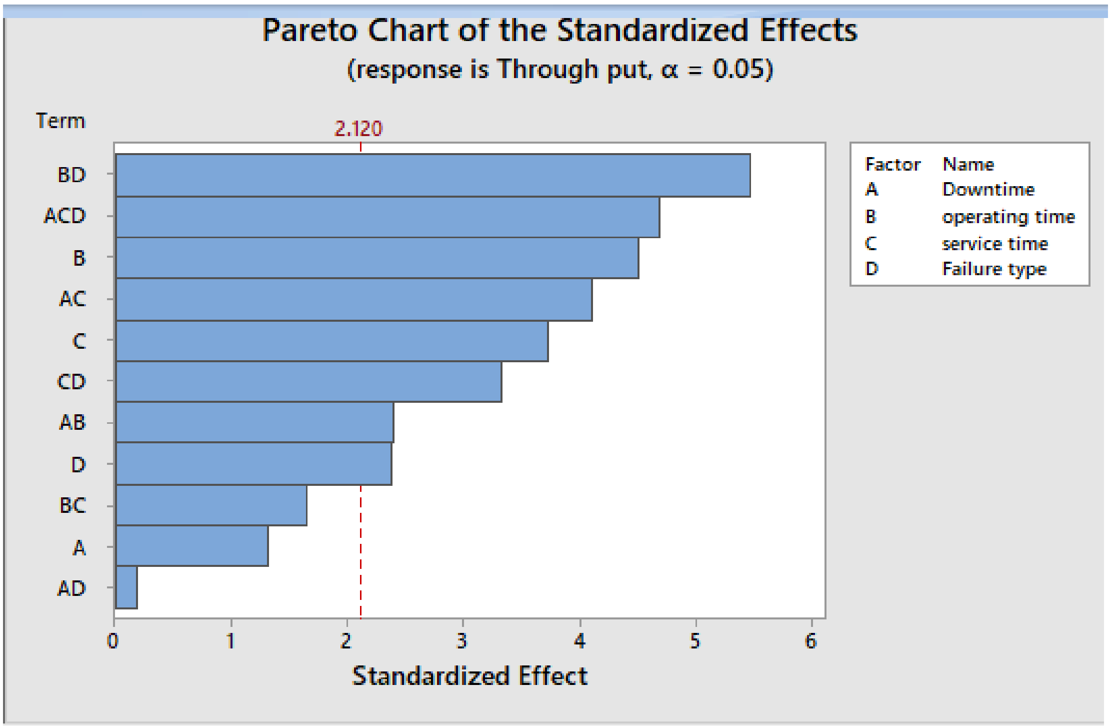


Figure 7 Effects pareto for throughput.

4.8.3 Modelling Number of Failure

Referring to uncoded equation in appendix 5, Considering $Number\ of\ failure = y_2, downtime = x_1\ operating\ time = x_2, service\ time = x_3\ \ Failure\ type = x_4$

$y_2 =$ 5.00 +0.019x_1 - 0.327x_2+0.0072x_3 - 2.00x_4-0.00089x_1x_2 - 0.000592x_1x_3 - 0.047x_1x_4 + 0.00318x_2x_3 + 0.238x_2x_4- 0.01259x_3 x_4+ 0.000709x_1 x_3x_4...........(10)

4.8.4 Effects Pareto for Number of Failures

According to Figure 8, the magnitude and the importance of the effects of independent variables on the dependant variable y_2 is illustrated on the pareto chart bars. The absolute value of effects of operating time is so large as it crosses the reference line of statistical significance. It is however difficult to establish its effects hence need for Normal probability plot probability plot of standardized effects in order to examine the magnitude and the direction of the effects on one plot. Probability plots of standardized effects enables researcher to gain comprehensive understanding of the factors influencing number of failures in tea processing plant. The process enables better-informed decision making and more effective optimization strategies.

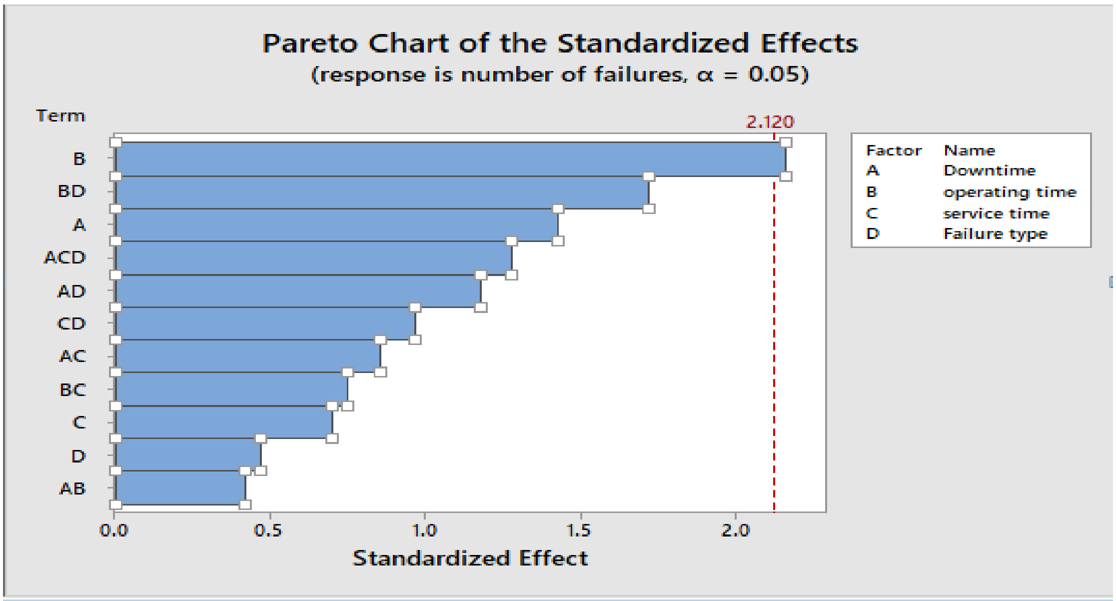


Figure 8 Effects pareto for number of failures.

4.9 Optimize the Maintenance Model of Critical Equipment in Tea Industry

The process involved choosing of a parameter that would likely be affecting outputs. $\boldsymbol{x}$ variables were chosen, and their distribution checked which were all established to follow a normal distribution. Their initial Means for x_1, x_2, x_3 , x_4, were confirmed to be 14.11, 12.57, 138.9 and 0.6786 respectively and corresponding standard Deviations of 24.72, 6.686, 13.6 and 0.4756. Before simulations, the model was checked and proved to be correct as illustrated in Appendix 4

4.9.1 Simulation of Results

Referred to Appendix 5 on simulation, all input variables (x) was still confirmed to be of normal distribution, the distribution of data, Percentiles and summary statistics were examined whether they meet the requirements and for the:

Number of failure regression, $N = 50{,}000$, $Mean = 1380.8$, $standard\ deviation = 206.95, Minimum = -2616.94$ and a $Median = 14$

Throughput regression, $N = 50{,}000$, $Mean = 7{,}269.29$, $Standard\ deviation = 5{,}746.07$, $Minimum = 86{,}415.68$, $Median = 6{,}983.55$ and $Maximum = 90{,}450.06$

4.9.2 Sensitivity Analysis

According to Appendix 6, for number of failures, the simulation indicated that expected number of failure values to fall outside the specification limits is 59.64 % corresponding to a process performance (CPK) of 0.0501 which is generally less than 1.33 as the statistically accepted value. The summary statistics being $N = 50{,}000$, $Mean = 2{,}388$Mean and $Standard\ deviation = 84{,}094$.

Simulation results indicated that 83.06% of through put values is expected to fall outside the specification limits with a corresponding process performance (CPK) of -0.0291, way less than the generally accepted minimum value of process performance (CPK) of 1.33. The summary statistics being: $N = 50{,}000$, $Mean = 15{,}450.72$, and $Standard\ deviation = 27{,}389.55$.

Identifying the root cause(s) of the low CPK value is crucial for implementing corrective actions to improve process capabilities. Addressing root causes of high percentage of out-of-spec data improves process performance and ensuring product quality.

4.9.3 Optimization of Maintenance Parameters

On optimizing parameters as illustrated in Appendix 7 and based on the two models for y variables, the inputs were confirmed as x_1, x_2, x_3, x_4. They were all checked for distribution which was again established to be of normal. The means for x_1, x_2, x_3, x_4 was generated as 0.012952, 3.5885, 0.08229 and 0.993556. All their low values were 0 while their corresponding high values were 30, 12, 240 and 1.

For number of Failure, after optimizing number of failures using new input settings, simulation produced 0.00% values of number of failures to fall outside the specification limits and the corresponding process performance figure (CPK) of 2.98 as the best considering the accepted minimum value is 1.33. The corresponding optimized results generated summary statistics of N=50,000, Mean=2.1483, standard deviation=0.213139, minimum=0.99706, median=2.1452 and maximum value=32,721. The evaluated percentiles were, 0.1^{st} =1.3953, 0.5^{th} =1.5416, 1^{st} =1.799, 5^{th} =1.799, 10^{th} =1.888, 90^{th} =2.4117, 95^{th} =2.5007,99^{th} =2.6931, 99.5^{th} =2.7692, 99.9^{th} =2.9349 (see Appendix 7).

For throughput, optimizing using new input settings of x_1, x_2, x_3, x_4 as 1.3334:0.000391, 9.9963:0.14972, 2.5845:6.3553, 0.99986:0.7138 respectively with a search Range of all low of 0, corresponding highs of 5, 10, 10 and 1 respectively in simulation gave 0.00% values of throughput to fall outside the specification limits and the corresponding process performance (CPK) figure of 2.43 as the best putting into consideration the accepted minimum value is 1.33. Percentage outside specification have strong negative correlation. There might be a direct correlation, however, other factors such as process variability, measurement error or external factors could influence the interdependency among the two variables.

The generated summary statistics being, N=50,000, mean=9,301.72, standard deviation=159.046.

4.10 Identification of a Critical Equipment in Tea Processing Plant

The findings on this research, optimization of maintenance management in tea industry which was a case study of Litein Tea Factory in Bureti sub-county of Kericho County revealed that the factory has 7 processing units. It was established from the maintenance records of the factory that most breakdown are mainly significant in the withering, Maceration, CTC, CFU, Drying, sorting and packing. It was not possible to pick on the most critical processing unit by mere observation hence prompting Failure mode effect analysis mode by use of Minitab application to compute the most critical of the seven. Therefore, through research and assessment, the chosen equipment met the specific needs considering it having significant consequences on production and product quality.

Failure mode and effect analysis with an application of Minitab software was used to compute criticality index among the seven processing units in the plant. Existing failure modes was characterised by looseness in connections, breakdowns, crushing and poor aeration. The singled out potential failures had effects on slowing down production processes, causing downtimes and ultimate drop in production. Upon analysis, the severity index was computed, and scores based on the responses guided by structured questions in the questionnaires. In a scale of 1-10 where 10 is the highest while 1 was considered lowest respectively, the processes were scored between 1 and 7 as the severity ratings. On the Potential causes, a close observation on each breakdown in each processing unit indicated that it causes the unit: drop in machine efficiency and effectiveness, machine failure, drop in process production as well as reduction in availability.

Current controls, in overall the commonest controls installed in the production units are the circuit breakers, switch gears and sirens. Occurrence rating, this is an index awarded critically on a scale of between 1 and 10, 1 considered to be the highest and 10 the lowest respectively whereby the processing machine was scored between Detection rating, which was on the scale of between 1 to 10, 10 being the poorest whereas 1 is the highest and the unit scored between 6 and 8. Finally, the RPN being the product of severity, occurrence and detecting rating for each machine was calculated and ranked based on their risk priority number as tabulated in Table 12.

Table 12: Level of criticalities for factory processing units

Serial Number	Processing Unit	Risk Priority Number
1	Cutting Tearing Curling (CTC)	252
2	Maceration	140
3	Withering	63
4	Fermentation (CFU)	48
5	Drier	32
6	Sorting	14
7	Packing	7

According to Table 12, all processing unit were awarded their respective Risk Priority index numbers generated from Failure Mode and Effect Analysis (FMEA). The highest index indicates a processing unit which is the most critical production unit identified as CTC with an index of 252. As per the main objective of the research, once a critical equipment was identified, regression model was to be established and further carry out an optimization process for the maintenance parameters.

4.11 Developing a Model Formulation for a Critical Equipment

Applying Minitab 17, statistic on the collected data was carried out first to design the experiment using factorial. The designed experiment was 2 level factorials with 6 factors and 28 runs representing the selected number of days the data was primarily collected. The option was taken based on the choices available in the created factorial design display available in Minitab 17 application and as a way to increase the power of the hypothesis test. Anova was carried out to establish the statistical significance of the population by application of P-value in comparison to the established value of $\alpha = 0.05$. It was however realized from the Anova that all P-values were less than the significance level hence need to increase the power of hypothesis test by generally reducing the standard deviations by optimizing the maintenance parameters, so as to increase possible power of hypothesis test. The attribute of this test is helping not to reject the null hypothesis over the alternative one.

Define custom factorial design was carried out where the 4 factors namely: Downtime, operating time, number of failure and operating time had their low and high values specified before allowing it to run in order to generate the regression equation.

4.11.1 Values of Probability Measures for Maintenance Parameters

The probability plot for each variable for 28 runs was computed again by the application of Minitab and the respective values for each maintenance parameter indicated value for the 6 variables was found to be less than 0. 005. In designing, 28 runs were chosen instead of based on the principle of fractional factorial designs. The design allowed for the exploration of a number of factors while reducing the number of experimental runs needed hence achieving efficiency both in time and resource constrains without compromising on the quality of the results. Other statistical measurements considered are their means and standard deviation respectively as illustrated in Table 13.

Table 13: Values of Probability Measures for Maintenance Parameters

Measurement	Throughput	No of failure	Service time	Operation time	Downtime	Failure time
Mean	5930	1.25	138.9	12.57	14.11	0.6786
Standard deviation	3031	1.506	134.6	6.686	24.72	0.4756
Number of runs	28	28	28	28	28	28
Ad	2.776	2.193	1.586	7.097	4.185	5.735
P-value	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005

4.11.2 Factorial regression equation for Throughput

Analysis of variance for the Throughput model generated a summary that confirmed on the goodness of fit statistics as illustrated in appendix 5 and generate an S value of 1302.66, Root means square (R^2) of 89.06 % and R^2(adj) of 81.53 % as illustrated in Appendix 2

4.11.3 Factorial regression equation for Number of failures

According to appendix 3, analysis of variance for Number of failure model generated a summary that confirmed on the goodness of fit statistics as illustrated in Appendix 5 and generated an S value of 1.35947, Root means square (R^2) of 51.72.06% and R^2(adj) of1 8.53% (See Appendix 3)

4.12 Optimize the Maintenance Model

Once models were developed for the two dependent variables y_1 and y_2, settings of the independent variables x_1, x_2, x_3 and x_4 were adjusted to establish how changes affected the responses. Response optimization was then interpreted in conjunction with the relevant general objective of the research (Unver & Gamgam, 1999).

4.12.1 Definition of Model

Applying companion by Minitab, the generated regression model was defined for both the Number of failure and the system's through put respectively. The correlation the corresponding Y and X variables was checked and found to be linear as the curve was also identified to be normal (see Appendix 4).

4.12.2 Simulation of the Results

The simulation process of the results was carried out using Monte Carlo simulation method where all the pointed variables in each case was integrated in order to achieve the set outcomes. The summary standards were ascertained by confirming the distribution of the data in order to check the extend of data meeting the statistical requirements as seen in Table 14.

Table 14: Simulation results for the regression models

Statistical measure	Number of failures	Through put
N	50,000	50,000
Mean	1 3808	7,269
Standard deviation	2 0695	5,746.07
Minimum	-26.1694	-86,415.68
Median	1.4031	6.983.55
Maximum	25.7624	90,450.06

4.12.3 Sensitivity Analysis

The analysis confirms if the process performance is within the generally accepted limits as well as the data percentage outside the specification as illustrated in Table 15.

Table 15: Sensitivity Analysis

Output (Y)	Process performance	Percentage outside specs.
Number of failures	0.0501	59.64%
Throughput	-0.0291	83.06%

The simulated results indicated that highest percentages of specifications outside were expected. The limits in each case were so high and the process performance (CPK) was way below the generally accepted minimum of 1.33. Hence the need to carry out parameter optimization for both throughput and number of failure regression models so that the percentages outside specification be brought to statistically accepted values which are 0.00% or close.

4.12.4 Optimizing Maintenance Parameters

All the X variables were again defined, identified, and confirmed to be exhibiting the characteristics of normal distribution curve. The mean and standard deviation of maintenance parameter is fed in Monte Carlo simulation in Minitab workspace. This process established the relationship of each parameter again to be in compliant with of normal curve distribution mode. The correlation between dependent variables (y) identified as throughput and the number of failures, and the x variables, namely downtime, Failure time, service time and type of failure are in each case established to be linear. The results were the simulated to give a bar graph (see Appendix 7).

By analysing the summary statistics, the insight into effectiveness of maintenance practices and identifying areas for improvement in the tea processing plant (see Table 16).

4.12.5 Summary Statistics

Table 16:2 Statistical Summary

Statistical measure	Number of failures	Through put
N	50,000	50000
Mean	13808	7269.29
Standard deviation	20695	5746.07
Minimum	-26.1694	-86415.68
Median	1.431	6983.68
Maximum	257624	90,450

Optimization of the input (X) variables was done first by considering the analysis of their means as illustrated in Table 17. By analysing statistical measures, performance benchmark to assess the effectiveness of maintenance strategies. The priority areas for improvement to optimize equipment reliability, availability and relative cost reduction is realized.

Table 17:3 Optimization of the Input Means

Input X	Current	Low	High
Downtime	0.012952	0	30
Operating time	3.5885	0	12
Service time	0.08229	0	240
Failure type	0.993556	0	1

Effecting the above changes and running simulation using the Monte Carlo simulation, some improvements was considerably achieved as in Table 18.

Table 18:4 Simulated Results of the First Optimized Parameters

Output (Y)	Process performance	Percentage outside specifications
Through put	1.17	0.05%
Number of failures	2.98	0.00%

From the Table 17 results, the process performance of the through put was still short of the minimum acceptable value of 1.33 hence the need for sensitivity analysis. The process indicates that the process is not meeting the desired quality or efficiency and suboptimal operating procedures or quality control issues.

With the above setting, the carried-out sensitivity analysis indicated the performance of -04167 and the expected percentage of through put values outside the specifications to be 90.66% hence ruling the possibility of the optimized parameters being acceptable as being way below the minimum accepted performance value of 1.33 and at least lower than 25% of through put values being outside the specification. The results therefore indicated that another sensitivity analysis should be carried out. The summary statistics given below therefore could not hold. The results suggest that different input scenarios to fine-tune model parameters, adjust decision-making criteria and enhance accuracy needed.

Table 19: Throughput Summary Statistics

Statistical measure	Value
N	50,000
Mean	13,899.08
Standard deviation	2,643.44
Minimum	3,239.97
Median	13,888.3
Maximum	25,050.93

4.13 Sensitivity Analysis

A third sensitivity analysis carried out gave the results with through put process performance of 2.43 and the percentage through put values out of specifications to be

0.00% therefore validating the achieved results as for the optimum parameters to give optimum through put results as shown in Table 20.

Table 20: Model Assumption

Input name (X)	New setting	Search range Low	High	Previous Setting
Downtime	(1.3334;0.000391)	0	5	(0.658288;000391)
Operating time	(9.9963;0.14972)	0	10	(9.9997;0.14972)
Service time	(2.5845;6.3553)	0	10	(1.7827;6.3553)
Failure type	(0.999806;0.7134)	0	1	(0.999033;0.7134)

For all the input parameters, the distribution was considered as normal. Absence of comparative studies limit the depth analysis and the ability to draw direct comparisons with existing research however the research fills a gap as it offers new perspective in the field.

Larger sample size generally provides greater statistical power and confidence. With more data, more accurate inference about the sensitivity of the optimization model to different parameters. More than 2 sensitivity analysis in regression models provided a more comprehensive understanding of factors influencing maintenance performance.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter provides interpretation of findings based on the evidence and their inferences along with actionable understanding of the objectives. This thesis delves into the intricate domain of maintenance performance measurement, focusing specifically on the case study of Litein Tea Factory. Through an in-depth discoveries of maintenance performance measurements of a critical equipment, the study endeavoured to shed light on key factors influencing maintenance efficiency and effectiveness in tea processing plant through evaluation of a mathematical model and optimizing it for best practices.

5.2 Conclusions

Based on the data collected from Litein Tea Factory and evidence in the presented findings of specific objectives generated from interrelations of maintenance parameters, the research conclusively established optimized maintenance measurements of identified critical equipment in tea processing industry. From the findings the researcher concluded that Crush Tear Curl (CTC) is the most critical processing unit in the production of tea based out of the failure mode effect analysis. It was established to have a criticality index of 252 as a factor of severity, occurrence and detection rating. The process took a number of stages stating with observation and the interrogation of section foremen as well as extraction of relevant information from the existing periodic processing data. Reports and documentation were prepared within the stipulated. Factorial regression by use of Minitab 17 in order to give the interrelationship between the dependent (Y) and independent(X) variables was generated. Y variables were identified as the daily factory throughput and the failure time respectively whereas the independent (X) was identified as the downtimes, operating times, service times and the failure type. Based on the generated models, it was concluded that throughput was established to have response for 1-way interaction with positive effects of +513, +308, on downtime and service time, while negative effects of -643.6 and -2816 on operating time and failure type respectively. In the 2-way interaction, it has positive effect of: +48.48, +725, +2.89, +0.6680 on: service time with Failure type, operating time with Failure type, Downtime with service time, operating time with Failure type while having negative effects of -2.334, -460, -4.90 on downtime with service time, Downtime with failure type, Downtime with operating time. Similarly, number of failures model, response for 1-way interaction has positive effects of +0.09, +0.0072 for downtime and service time, while negative effects of -0.327 and -2.00 on operating time and failure type respectively. For the 2-000592, -interaction, it has positive effects of: +0.003180, +0.238 on Downtime with service time, operating time with Failure type and negative effects of -0.00089, -0.000592, -0.0467, -0.01259 on downtime with operating time, Downtime with service time, Service time with Failure type and, +0.007 on 3-way interaction consisting of is Downtime with Failure type and Service time. This was undertaken in order to generate the regression model. The generated model summary was characterized by factors indicated in R^2 values of 89.06% and 51.72% for throughput and number of Failure models respectively while their corresponding s values were 1302.66 and 1.35947. When regression was simulated, analysis indicated that percentage of data outside specification were 59.64% and 83.06% for Number of failure and throughput respectively while corresponding Process Performance (CPK) values were 0.0501 and -0.0291. For both variables, the effects of Pareto were respectively α=0.05 -2.120 respectively. Further their standard deviations and the means were relatively high.

Using Companion by Minitab worksheet, independent variables namely Downtime, operating time, Service time and failure type had their levels defined all with normal distributions while the respective lower of 0 and upper limits of 30,12,240 and 1 respectively in order to define levels under which optimization range should lie within. Their current means was set at 0.01295,3.5885,0.08229 and 0.9935 in the order of downtime, operating time, service time and failure type respectively. The process of optimization was successfully carried out using Monte Carlo simulation. Each dependent variable was simulated in order to confirm the levels of process performance and the respective percentage of values out of specifications. In the first simulation run, number of failures had the process performance of 0.0501 while the percentage out of specification was 59.64%, a mean of 2.388 and standard deviation of 8.4098 while that of Through put model was -0.0291 and percentage out of specifications of high of 83.06%, mean of 15,450 and standard deviation of 27,389.55. The guiding principle being no value of data should be outside the specification hence 0 % while process performance should be more than 1.33 thus the need to perform further sensitivity analysis. This inconsistency prompted subsequent processes to be carried out as illustrated in worksheet in Appendix 6. The second results for the Number of failures successfully gave a process performance of 2.98, % of data outside the specifications of 0.00%, mean of 2.1481 and standard deviations of 0.213139 while through put produced a process performance of 1.17, 0.05% of data still outside the specifications, mean of 9300.19 and standard deviation of 261.41. The process could not meet the minimum specifications hence the need to perform third process of sensitivity analysis for best statistical results.

The general objective of optimizing maintenance performance measurement in a critical equipment in tea processing plant was empirically addressed through comprehensive examination maintenance performance measurements. Focusing on the key aspects, the study provided quality insights and actionable recommendations for enhancing maintenance effectiveness, efficiency, availability and overall productivity.

5.3 Recommendations

Having established existence of gaps in the field of study, this research made recommendations by ensuring strategies to put in place equipment availability, efficiency and overall improvement of productivity by identifying critical equipment, evaluating maintenance measurement model and optimizing it for best practices.

5.3.1 Operation and Maintenance

Based on the findings, the study recommends that cutting Tear Curl (CTC) is the most critical equipment in the tea processing. The uncoded regression detailing the interrelationship between the depended variables being the trough put and the number of failures against the independent variables identified as downtime, operating time, service time, and the failure type was established as a normal and to have a linear relationship. Optimization of maintenance performances measurement is achievable through minimizing or maximising process performance with minimum acceptable standard of 1.33 and ensuring percentage out of specification data being 0 or closer to 0 as much as possible. There are desirable optimized parameters in maintenance performance measurement in tea processing of 83.06% and to achieve the optimal number of failures in the process plant, there is need to reduce the value of the number of downtimes in through put model by -20% in order to have the value of process performance rise up from down -0.0291 to 2.43 and data percentage out of specification from high of 83.06% to significant low of 0.00% while changing all independent variables in the Number of failure model so that from process performance of 0.05 to 2.98 and data percentages out of specifications of 59.64% to 0.00%..

5.3.2 Future Study

By addressing these areas in future research, a more holistic understanding of holistic scope in performance measurement optimization in tea processing and can be inferred in other production plants. The study makes recommendations that consideration to maximize R^2 values to at least 85% in optimizing maintenance performance measurements parameters. Research may also consider making comparison maintenance measurement optimization strategies across multiple tea processing plants to identify best practices and variations in effectiveness. Conducting a comprehensive Cost-Benefit analysis of different maintenance optimization approaches may give more insights into their economic viability and return on investment.

REFERENCES

Abate, T. M., Dessie, A. B., & Mekie, T. M. (2019). Technical efficiency of smallholder farmers in red pepper production in North Gondar zone Amhara regional state, Ethiopia. *Journal of Economic Structures*, *8*(1), 1-18.

Abhiram, G., Jinthushayi, S., & Withanage, N. S. (2018). Optimization of feeding rate and pressure of Orthodox roller in black tea production ,Uva Wellassa,Sri Lanka. *AGRIEAST: Journal of Agricultural Sciences, 12*(1), 16-25.

Barringer, P. H., & Barringer, P. E. (2006). An overview of reliability engineering principles. In *Penn Well conferences & Exhibitions Houston* (pp. 1-8). Texas: Beaumont.

Bellgran, M., & Safsten, K. (2010). *Production Development design and operation of production system.* UK: Springer.

Bulali, S. J. (2014). *Determination of energy efficiency in black tea processing A case study of Kenya Tea Development Agency, Nairobi* (Master of Arts Thesis, Univeristy of Nairobi).

Campbell, R., Brewer, P., & Mills, T. (1997). Designing an information system using activity-based costing and the theory of constraints. *Journal of Cost management*, *11*, 16-25.

Du, J. (2008). *Evaluation of equipment reliability, availability and maintainability in an oil sands processing plant* (Doctoral dissertation, University of British Columbia).

Ebrahimi, A. (2010). *Effect analysis of Reliability, Availability, Maintainability and Safety (RAMS) Parameters in design and operation of Dynamic Positioning (DP) systems in floating offshore structures* (Master's Degree thesis, Royal Institute of Technology).

Eti, M. C., Ogaji, S. O. T., & Probert, S. D. (2006). Reducing the cost of preventive maintenance (PM) through adopting a proactive reliability-focused culture. *Applied energy*, *83*(11), 1235-1248.

Goode, K. B., Moore, J., & Roylance, B. J. (2000). Plant machinery working life prediction method utilizing reliability and condition-monitoring data. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, *214*(2), 109-122.

Gupta, R., & Dey, S. K. (2010). Development of a productivity measurement model for tea industry. *ARPN Journal of Engineering and Applied Sciences*, *5*(12), 16-25.

Hansen, R. C. (2002). *Overall equipment effectiveness: a powerful production/maintenance tool for increased profits*. Industrial Press Inc.

Hasanbeigi, A., & Price, L. (2011). *Industrial energy audit guidebook: Guidelines for conducting an energy audit in industrial facilities*. University of California.

Kostina, M. (2012). Reliability management of manufacturing processes in machinery enterprises (PhD Thesis, Tallinn University of Technology).

Lai, R., & Garg, M. (2012). A detailed study of NHPP software reliability models. *J. Softw.*, *7*(6), 1296-1306.

Lanjewar R.W. (2008). Evaluating parameters for turning of AISI 304 austenitic stainless steel on auto sharpening machine.

Lanjewar, R. W., Saha, P., Datta, U., Banerjee, A. J., Jain, S., & Sen, S. (2008). Evaluation of machining parameters for turning of AISI 304 austenitic stainless steel on auto sharpening machine. *Scientific and Industrial Research* , *67*(4), 282-287.

Maina, E. W. (2018). *Influence of Strategic Management Practices on Competitiveness of Kenyan Tea* (Doctoral dissertation, Jkuat-COHERED).

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and multidisciplinary optimization*, *26*, 369-395.

Marler, R. T., Arora, J. S., Yang, J., Kim, H. J., & Abdel-Malek, K. (2009). Use of multi-objective optimization for digital human posture prediction. *Engineering Optimization*, *41*(10), 925-943.

Masiyazi, L., Chiteka, K., Dewa, M. T., & Museka, D. (2014). Productivity improvement through Process optimization: case study of a plastic manufacturing and sales company. In *Int'l conference Image processing, computer and industrial engineering (ICICIE 2014)*.

Mathew, J., & Mathew, S. G. (2015). Analysis of Failure Modes and Selection of Maintenance Strategy for Vital Machines in a Tea Industry. *International Journal of Science Technology & Engineering*, *2*(05), 121-125.

Mbohwa, C., & Mwanza, B. (2016, March). Evaluating Maintenance Strategies Effectiveness on Overall Equipment Utilization. In *Proceedings-International Conference on Industrial Engineering and Operations Management, Kuala Lumpur, Malaysia* (pp. 2323-2332).

Melican, N. J. (2004). Processing Tea for Lower Cost and Better Quality. *Tankariwala, NF Technical Session*, *2*, 63-71.

Nagaraj, H. (2015). *Preliminary energy study conducted at Arrapetta Tea Factory*. Retrieved from https://www.scribd.com/document/386908081/EAM3-pdf

Ng'era, S. M. (2013). *How Maintenance Practices Influence Manufacturing Performance in Ktda Managed Factories* (Doctoral dissertation, University of Nairobi).

Ogage, L. K. (2015). *Operations Management and performance of Kenya Tea Development Agency managed tea factories in Kenya* (Doctoral dissertation, University of Nairobi).

Ojukwu, C. O. Maintenance Management Practices on Organizational Performance of Tertiary Hospitals in Enugu and Anambra States. *National Research and Innovation Academia*, *85*(5), 46-61.

Parida, A. (2006). *Development of a multi-criteria hierarchical framework for maintenance performance measurement: Concepts, issues and challenges* (Doctoral dissertation, Luleå tekniska universitet).

Parida, A., & Chattopadhyay, G. (2007). Development of a multi- criteria hierarchical framework for maintenance performance measurement (MPM). *Journal of Quality in maintenance Engineering*, *13*(3), 241-258.

Parida, A., & Kumar, U. (2006). Maintenance performance measurement (MPM): issues and challenges. *Journal of Quality in Maintenance Engineering*, *12*(3), 239-251.

Parida, A., Chattopadhyay, G., & Kumar, U. (2005). *Multi criteria maintenance performancemeasurement: a conceptual model*. Proceedings of the 18th International Congress ofCOMADEM, 31 August-2 September, Cranfield, pp. 349-56

Pintelon, L., & Van Puyvelde, F. (2006). *Maintenance decision making*. Acco.

Ravichandran, M. T., & Mahindrakar, A. D. (2010). Robust stabilization of a class of underactuated mechanical systems using time scaling and Lyapunov redesign. *IEEE Transactions on Industrial Electronics*, *58*(9), 4299-4313.

Srivastava, N. K., & Mondal, S. (2016). Development of framework for predictive maintenance in Indian manufacturing sector. *International Journal of Services and Operations Management*, *24*(1), 73-98.

Swanson, L. (2001). Linking Maintenance Strategies to performance. *International Journal of Production Economics, 70*, 237-244.

Taulo, J. L. (2007). *A multi-objective optimization tool for the Malawian tea industry with sustainability considerations* (Doctoral dissertation, Stellenbosch: Stellenbosch University).

Weber, A., & Thomas, R. (2006). Key performance indicators: measuring and managing the maintenance function. *Ivara Corporation*, 1-16.

Yan, J. (2014). *Machinery prognostics and prognosis oriented maintenance management*. John Wiley & Sons.

Zhou, X., Xi, L., & Lee, J. (2007). Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation. *Reliability engineering & system safety*, *92*(4), 530-534.

APPENDICES

Appendix 1: Research Questionnaire

I am a Masters student at Moi University. You are kindly invited to participate in ongoing research which seek to explore into the optimization of maintenance in a critical equipment in tea processing. This research questionnaire seeks to solicit your valued opinion, to aid the study. Please fill in the required information in the spaces provides by placing a tick (√) where appropriate.

Section I. RESPONDENTS DETAILS

1. Please select the highest level of education completed in respective field of study.

Field of study	Certificate	Diploma	Degree	Post graduate
Engineering				
Computer Studies				
Business				
Medical				
Law				
Others				

2. How long have you been working in this organization?

a) Less than a year ( )

b) 1-5 years ( )

c)6-10 years ( )

d) More than 10 years ( )

Section II: Severity of the processing unit.

In a scale of 1 to 10, where 10 is the highest and 1 being the lowest; What is the severity of the failure in the following processing unit.

PROCESS	MACHINE	SEVERITY
Withering	Conveyor	
	Fans	
	Leaf sifting	
Leaf maceration	Shredder	
	Rotor vane	
	PVC conveyor	
Cutting Tear Curl (CTC)	Axial pitch adjustment	
	Cage unit	
	Crusher	
	Rollers	
Continuous fermentation	Oxidation chamber Ball breaker	
Convectional drying	Floats	
	Pre-drying	
	Tray circuit	
	Strainers	
Sorting	Pre-sorter screens	
	Vibro-screens	
Packing	Bucket Elevator	
	Packing hopper	
	Chains and sprockets	

Section III: Frequency of failure mode

In a scale of 1 to 10, where 10 is the highest and 1 being the lowest. How frequent is the failure modes likely to occur in the corresponding process unit.

Processing Unit	Loose tension	Breakdown	Crushing	Wear and Tear	Breakage	Bluntness
Withering						
Maceration						
CTC						
CFU						
Drier						
Sorting						
Packing						

Section IV: Detection control

In a scale of 1 to 10, where:10 is the poor detection,1 is the highest detection What is the ability of each control in detecting the failure mode.

Processing unit	Programmable Logic control	Control meters	Thermal mass flow meters	Alarms
Withering				
Maceration				
CTC				
CFU				
Drier				
Sorting				

Appendix 2: Failure Type

Analysis of Variance

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	11	220972909	20088446	11.84	0.000
Linear	4	54510429	13627607	8.03	0.001
Downtime	1	2923015	2923015	1.72	0.208
operating time	1	34329608	34329608	20.23	0.000
service time	1	23397854	23397854	13.79	0.002
Failure type	1	9617273	9617273	5.67	0.030
2-Way Interactions	6	102112668	17018778	10.03	0.000
Downtime*operating time	1	9764851	9764851	5.75	0.029
Downtime*service time	1	28427601	28427601	16.75	0.001
Downtime*Failure type	1	57003	57003	0.03	0.857
Operating time*service time	1	4563404	4563404	2.69	0.121
Operating time*Failure type	1	50697633	50697633	29.88	0.000
Service time*Failure type	1	18666173	18666173	11.00	0.004
3-Way Interactions	1	37081252	37081252	21.85	0.000
Downtime*service time *Failure type	1	37081252	37081252	21.85	0.000
Error	16	27150665	1696917		
Lack-of-Fit	13	27140583	2087737	621.23	0.000
Pure Error	3	10082	3361		
Total	27	248123574			

Model Summary

S	R^2	R^2(adj)	R^2(pred)
1302.66	89.06%	81.53%	*

Coded Coefficients

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant		10154	1367	7.43	0.000	
Downtime	4282	2141	1631	1.31	0.208	12.78
operating time	-6097	-3048	678	-4.50	0.000	5.10
service time	-13345	-6672	1797	-3.71	0.002	28.72
Failure type	-6282	-3141	1319	-2.38	0.030	25.06

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Downtime*operating time	-3526	-1763	735	-2.40	0.029	5.00
Downtime*service time	-17650	-8825	2156	-4.09	0.001	25.26
Downtime*Failure type	-545	-273	1487	-0.18	0.857	27.18
operating time*service time	1925	963	587	1.64	0.121	2.58
operating time*Failure type	5802	2901	531	5.47	0.000	4.62
service time*Failure type	11435	5718	1724	3.32	0.004	28.99
Downtime*service time*Failure type	20158	10079	2156	4.67	0.000	33.17

Appendix 3: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	11	31.6796	2.8800	1.56	0.204
Linear	4	18.2507	4.5627	2.47	0.087
Downtime	1	3.7606	3.7606	2.03	0.173
Operating time	1	8.6334	8.6334	4.67	0.046
Service time	1	0.8908	0.8908	0.48	0.497
Failure type	1	0.3990	0.3990	0.22	0.648
2-Way Interactions	6	16.4506	2.7418	1.48	0.246
Downtime*operating time	1	0.3246	0.3246	0.18	0.681
Downtime*service time	1	1.3456	1.3456	0.73	0.406
Downtime*Failure type	1	2.5453	2.5453	1.38	0.258
Operating time*service time	1	1.0308	1.0308	0.56	0.466
Operating time*Failure type	1	5.4558	5.4558	2.95	0.105
Service time*Failure type	1	1.7287	1.7287	0.94	0.348
3-Way Interactions	1	3.0126	3.0126	1.63	0.220
Downtime*service time*Failure type	1	3.0126	3.0126	1.63	0.220
Error	16	29.5704	1.8482		
Lack-of-Fit	13	21.5704	1.6593	0.62	0.764
Pure Error	3	8.0000	2.6667		
Total	27	61.2500			

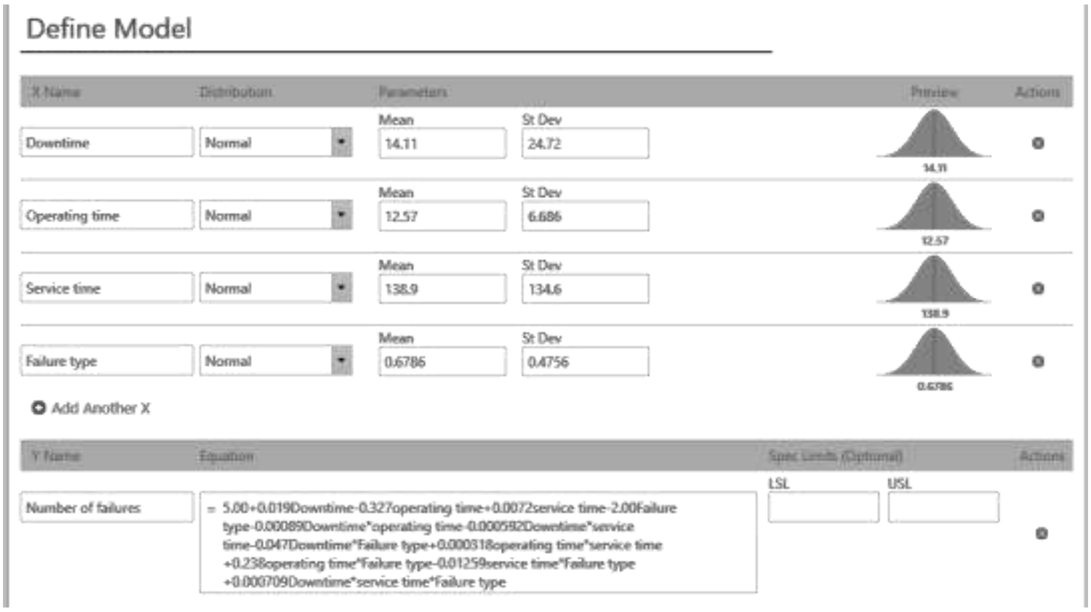
Model Summary

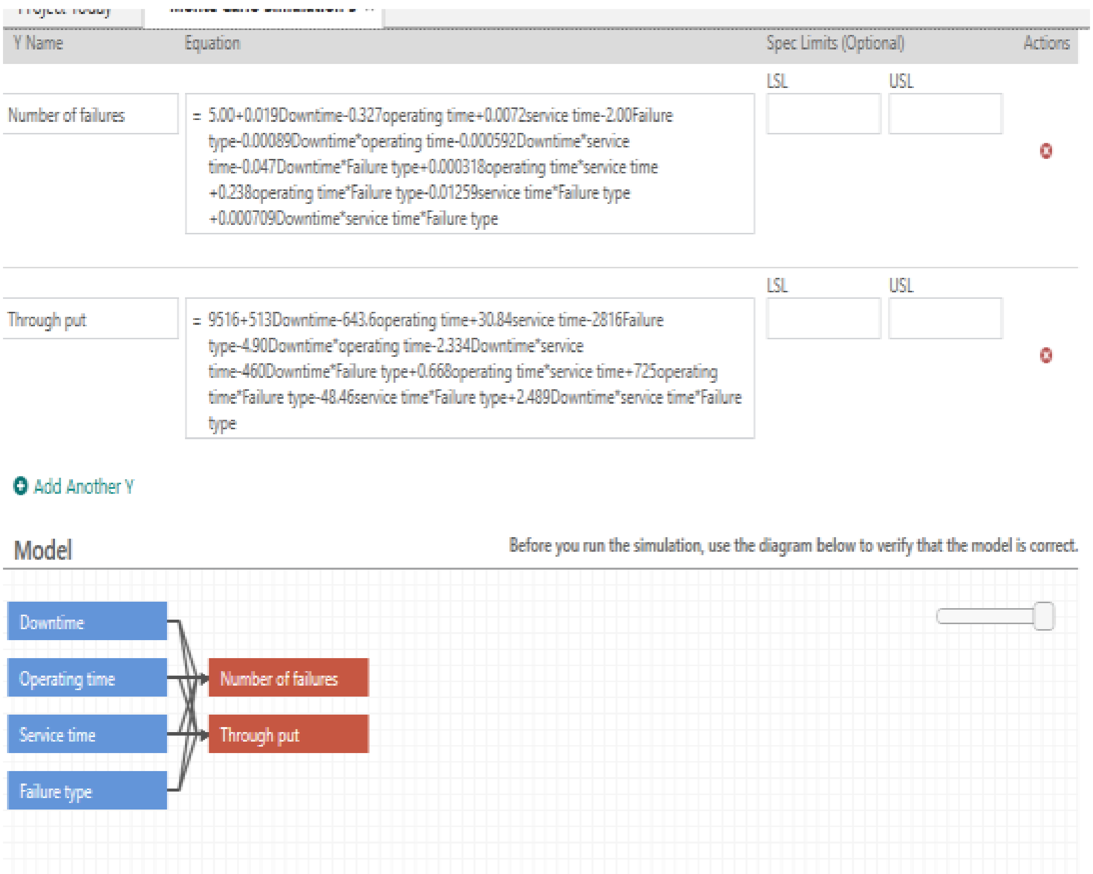
S	R^2	R^2(adj)	R^2(pred)
1.35947	51.72%	18.53%	*

Coded Coefficients

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant			0.52	1.43	0.37	0.718
Downtime	-4.86	-2.43	1.70	-1.43	0.173	12.78
Operating time	-3.057	-1.529	0.707	-2.16	0.046	5.10
Service time	-2.60	-1.30	1.88	-0.69	0.497	28.72
Failure type	1.28	0.64	1.38	0.46	0.648	25.06
Downtime*operating time	-0.643	-0.321	0.767	-0.42	0.681	5.00
Downtime*service time	-3.84	-1.92	2.25	-0.85	0.406	25.26
Downtime*Failure type	3.64	1.82	1.55	1.17	0.258	27.18
Operating time*service time	0.915	0.457	0.613	0.75	0.466	2.58
Operating time*Failure type	1.903	0.952	0.554	1.72	0.105	4.62
service time*Failure type	3.48	1.74	1.80	0.97	0.348	28.99
Downtime*service time*Failure type	5.75	2.87	2.25	1.28	0.220	33.17

Appendix 4: Modelling definition



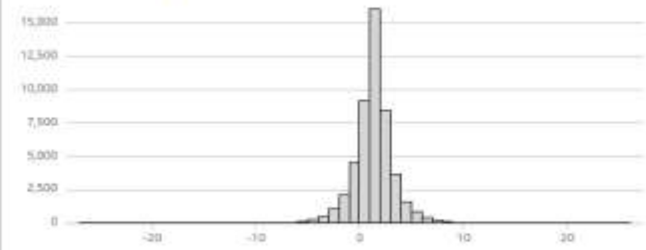


Appendix 5: Simulation of results

Simulation Results

Output (Y) All Outputs

Number of failures



Summary Statistics

N	50,000
Mean	1.3808
Standard Deviation	2.0695

Examine the distribution of the data and the summary statistics to determine whether they meet your requirements.

▾ Less Results

Capability

Specification Limits	
USL	—
LSL	—
DPMO	
>USL	—
<LSL	—
Observed Performance	
>USL	—
<LSL	—

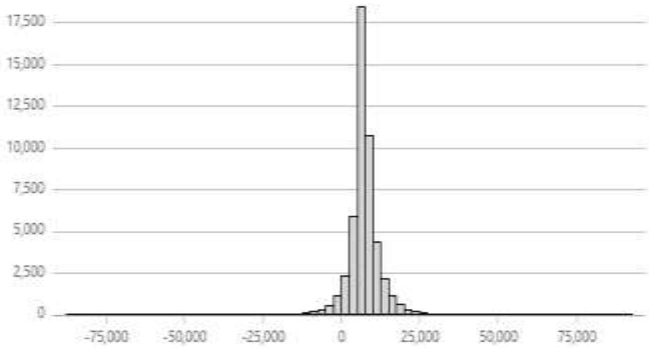
Summary Statistics

N	50,000
Mean	1.3808
Standard Deviation	2.0695
Minimum	-26.1694
Median	1.4031
Maximum	25.7624

Percentiles

0.1st	-9.8244
0.5th	-5.6344
1st	-4.3184
5th	-1.8503
10th	-0.818716
90th	3.4845
95th	4.5404
99th	7.411
99.5th	8.8496
99.9th	12.1839

Through put



Summary Statistics

N	50,000
Mean	7,269.29
Standard Deviation	5,746.07

Examine the distribution of the data and the summary statistics to determine whether they meet your requirements.

▾ Less Results

Capability

Specification Limits

USL	—
LSL	—

DPMO

>USL	—
<LSL	—

Observed Performance

>USL	—
<LSL	—

Summary Statistics

N	50,000
Mean	7,269.29
Standard Deviation	5,746.07
Minimum	-86,415.68
Median	6,983.53
Maximum	90,450.06

Percentiles

0.1st	-27,903.9
0.5th	-13,892.1
1st	-9,218.61
5th	-519.972
10th	2,361.23
90th	12,684.62
95th	15,937.94
99th	25,083.04
99.5th	29,504.92
99.9th	43,525.29

Model Assumptions

Inputs

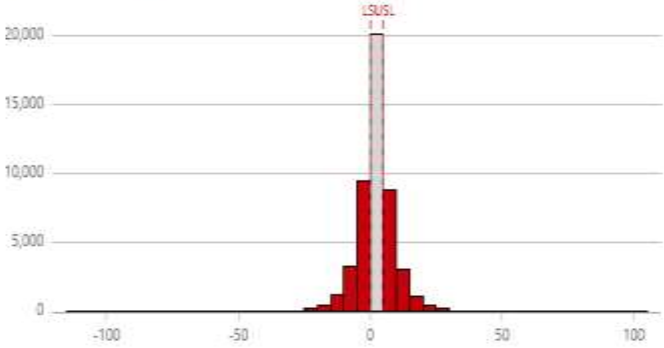
Name	Distribution	Settings
Downtime	Normal	(14.11; 24.72)
Operating time	Normal	(12.57; 6.686)
Service time	Normal	(138.9; 134.6)
Failure type	Normal	(0.6786; 0.4756)

Outputs

Name	Equation
Number of failures	5.00+0.019Downtime-0.327operating time+0.0072service time-2.00Failure type-0.00089Downtime*operating time-0.000592Downtime*service time-0.047Downtime*Failure type+0.000318operating time*service time +0.238operating time*Failure type-0.01259service time*Failure type+0.000709Downtime*service time*Failure type
Through put	9516+513Downtime-643.6operating time+30.84service time-2816Failure type-4.90Downtime*operating time-2.334Downtime*service time-460Downtime*Failure type+0.668operating time*service time+725operating time*Failure type-48.46service time*Failure type+2.489Downtime*service time*Failure type

Appendix 6: Sensitivity analysis

Number of failure



The simulation indicates that you can expect 59.64% of the *Number of failure* values to fall outside of the specification limits. This corresponds to a Cpk of 0.0501. A generally accepted minimum value of Cpk is 1.33.

Process Performance (Cpk)

0.0501

% Out of Spec

59.64%

Summary Statistics

N	50,000
Mean	2.388
Standard Deviation	8.4094

Capability

Specification Limits	
USL	5
LSL	0
DPMO	
>USL	289,400
<LSL	307,020
	596,420
Observed Performance	
>USL	14,470
<LSL	15,351
	29,821

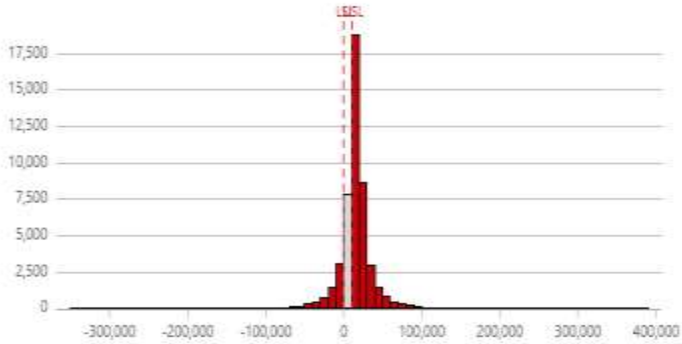
Summary Statistics

N	50,000
Mean	2.388
Standard Deviation	8.4094
Minimum	-114.982
Median	2.3396
Maximum	100.234

Percentiles

0.1st	-46.0983
0.5th	-28.7646
1st	-21.7339
5th	-9.8209
10th	-5.7511
90th	10.5463
95th	14.6669
99th	27.3347
99.5th	34.8122
99.9th	53.2601

Through put



The simulation indicates that you can expect 83.06% of the *Through put* values to fall outside of the specification limits. This corresponds to a Cpk of -0.0291. A generally accepted minimum value of Cpk is 1.33.

Process Performance (Cpk)

-0.0291

% Out of Spec

83.06%

Summary Statistics

N	50,000
Mean	15,450.72
Standard Deviation	27,389.55

▾ Less Results

Capability

Specification Limits	
USL	10,444
LSL	0

DPMO	
>USL	684,860
<LSL	145,760
	830,620

Observed Performance	
>USL	34,243
<LSL	7,288
	41,531

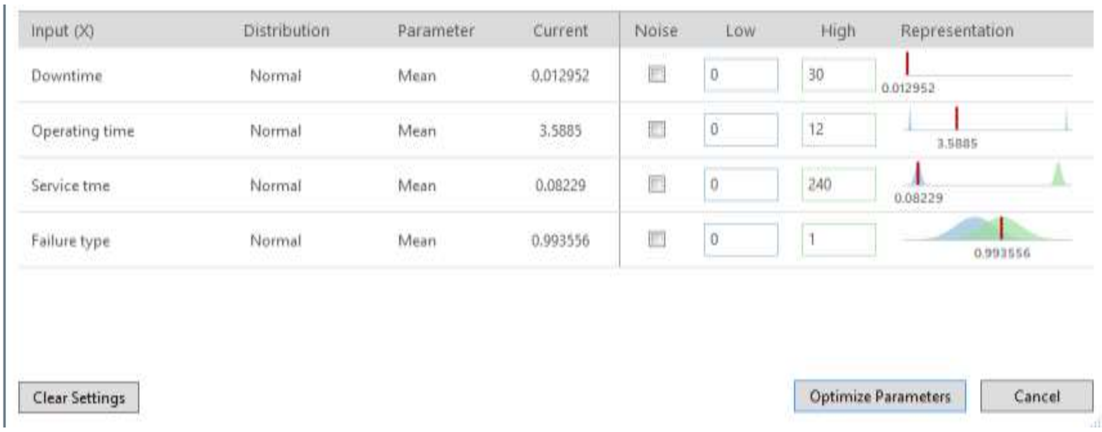
Summary Statistics

N	50,000
Mean	15,450.72
Standard Deviation	27,389.55
Minimum	-346,691.78
Median	15,579.29
Maximum	389,018.1

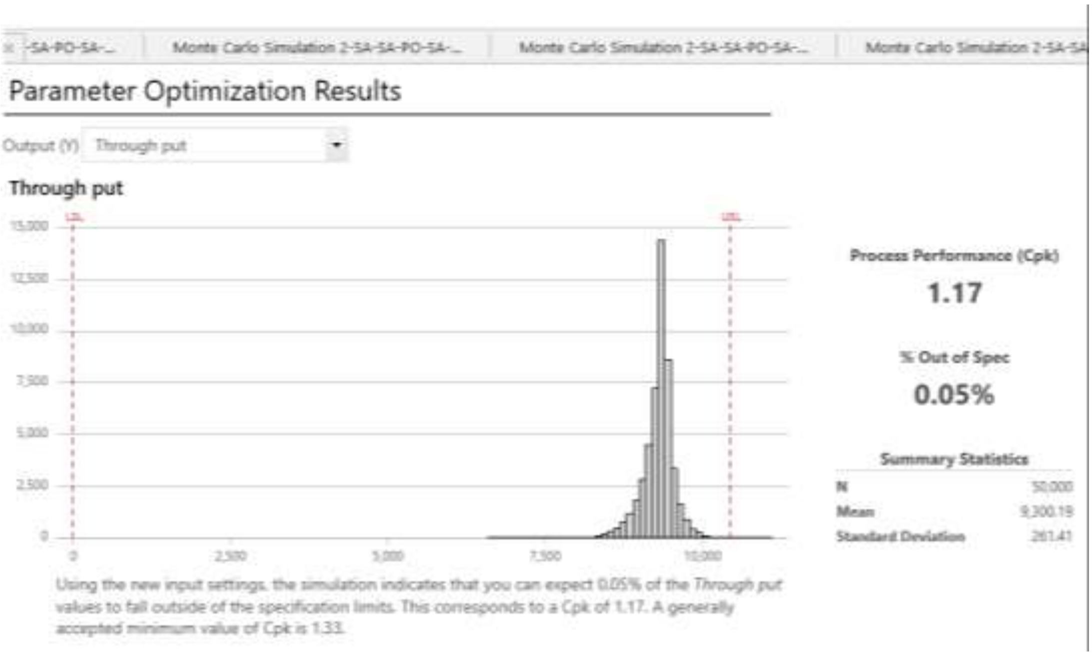
Percentiles

0.1^{st}	-160,586.49
0.5^{th}	-92,711.46
1^{st}	-69,748.13
5^{th}	-21,245.73
10^{th}	-6,615.95
90^{th}	36,975.22
95^{th}	53,130
99^{th}	103,626.24
99.5^{th}	130,027.55
99.9^{th}	204,617.8

Appendix 7: Optimization of maintenance parameters



Input (X)	Distribution	Parameter	Current	Noise	Low	High	Representation
Downtime	Normal	Mean	0.012952		0	30	0.012952
Operating time	Normal	Mean	3.5885		0	12	3.5885
Service tme	Normal	Mean	0.08229		0	240	0.08229
Failure type	Normal	Mean	0.993556		0	1	0.993556



Capability

Specification Limits

USL	10,444
LSL	0

DPMO

>USL	540
<LSL	0
	540

Observed Performance

>USL	27
<LSL	0
	27

Summary Statistics

N	50,000
Mean	9,300.19
Standard Deviation	261.41
Minimum	6,689.05
Median	9,342.18
Maximum	11,004.14

Percentiles

0.1^{st}	7,910.26
0.5^{th}	8,287.7
1^{st}	8,451.47
5^{th}	8,823.2
10^{th}	8,988.05
90^{th}	9,549.74
95^{th}	9,664.04
99^{th}	9,930.18
99.5^{th}	10,037.25
99.9^{th}	10,362.91

-SA-PO-SA-... | Monte Carlo Simulation 2-SA-SA-PO-SA-... | Monte Carlo Simulation 2-SA-SA-PO-SA-... | Monte Carlo Simulation 2-SA-SA

Assumptions

Optimization Goal: Maximize the Cpk of Through put

Inputs

Name	New Settings	Search Range		Previous Settings	Distribution
Downtime	(0.012952; 0.000341)	Low: 0	High: 30	(0; 0.000341)	Normal
Operating time	(3.5885; 0.058671)	Low: 0	High: 12	(3.651; 0.058671)	Normal
Service time	(0.08229; 5.2052)	Low: 0	High: 240	(0; 5.2052)	Normal
Failure type	(0.993556; 0.7134)	Low: 0	High: 1	(0.983397; 0.7134)	Normal

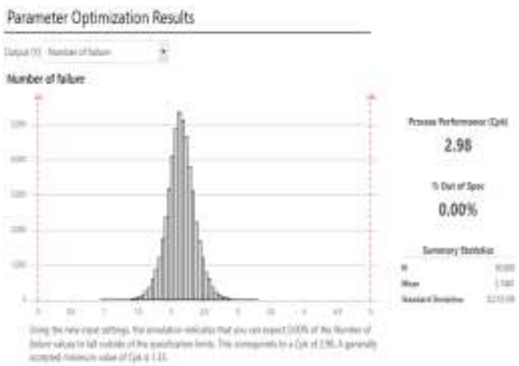
Outputs

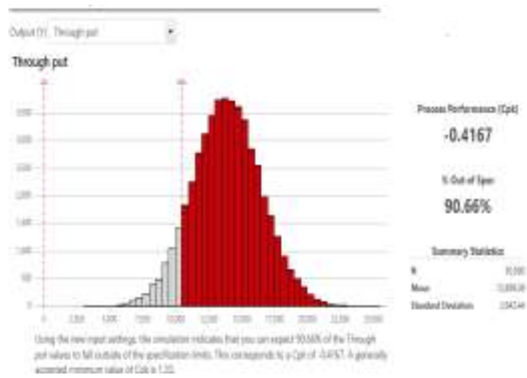
Name	Equation
Number of failure	5.000+0.09Downtime-0.327Operating time+0.00725Service tme-2.00Failure type-0.00089Downtime*Operating time-0.000592Downtime*Service tme-0.047Downtime*Failure type+0.000318Operating time*Service tme +0.238Operating tme*Failure type-0.01259Service tme*Failure type+0.0007Downtime*Service tme*Failure type
Through put	9516+513Downtime-643.6Operating time+643.6Operating time+30.84Service tme-2816Failure type-4.90Downtime*Operating time-2.334Downtime*Service tme-460Downtime*Failure type+0.668Operating time*Service tme+725Operating time*Failure type-48.46Service tme*Failure type+2.489Downtime*Service tme*Failure type

Next Steps

The Cpk is below the generally accepted value. Consider performing a **Sensitivity Analysis**, which demonstrates how changes to the variation of the inputs affect the variation of *Through put*.

Sensitivity Analysis





▾ Less Results

Capability

Specification Limits	
USL	5
LSL	0

DPMO	
>USL	0
<LSL	0
	0

Observed Performance	
>USL	0
<LSL	0
	0

Summary Statistics

N	50,000
Mean	2.1481
Standard Deviation	0.213139
Minimum	0.99706
Median	2.1452
Maximum	3.2721

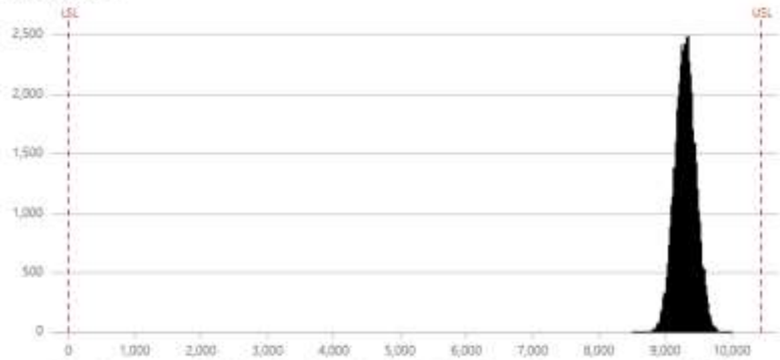
Percentiles

0.1^{st}	1.3953
0.5^{th}	1.5416
1^{st}	1.6209
5^{th}	1.799
10^{th}	1.888
90^{th}	2.4117
95^{th}	2.5007
99^{th}	2.6931
99.5^{th}	2.7692
99.9^{th}	2.9349

Sensitivity Analysis Results

Output (Y) Through put

Through put



Process Performance (Cpk)

2.43

% Out of Spec

0.00%

Summary Statistics

N	50,000
Mean	9,301.72
Standard Deviation	159.046

Using the new standard deviation values, the simulation indicates that you can expect 0.00% of the *Through put* values to fall outside of the specification limits. This corresponds to a Cpk of 2.43. A generally accepted minimum value of Cpk is 1.33.

Name	New Settings	Search Range		Previous Settings	Distribution
Downtime	(1.3334; 0.000381)	Low: 0	High: 5	(0.658288; 0.000381)	Normal
Operating time	(8.9993; 0.14972)	Low: 0	High: 10	(8.9997; 0.14972)	Normal
Service time	(2.5845; 6.3223)	Low: 0	High: 10	(1.7827; 6.3223)	Normal
Failure type	(0.999806; 0.1134)	Low: 0	High: 1	(0.999033; 0.1134)	Normal

Outputs

Name	Equation
Number of failure	5.000+0.09Downtime-0.327Operating time+0.0072Service time-2.00Failure type-0.00089Downtime*Operating time-0.000592Downtime*Service time-0.047Downtime*Failure type+0.000318Operating time*Service time +0.2380Operating time*Failure type-0.01258Service time*Failure type+0.0007Downtime*Service time*Failure type
Through put	8516+513Downtime-643.6Operating time+643.6Operating time+30.84Service time-2816Failure type-4.90Downtime*Operating time-2.334Downtime*Service time-460Downtime*Failure type+0.666Operating time*Service time+725Operating time*Failure type-48.49Service time*Failure type+2.488Downtime*Service time*Failure type

Next Steps

Although the Cpk is above the generally accepted value, you may want to perform a **Sensitivity Analysis**, which demonstrates how changes to the variation of the inputs affect the variation of Number of failure.

Sensitivity Analysis

Response: Number of failure

Inputs

Name	New Settings	% Change	Previous Settings	Distribution
Downtime	(0.012952; 0.000012)	-20%	(0.012952; 0.000015)	Normal
Operating time	(3.5885; 0.000263)	0%	(3.5885; 0.000263)	Normal
Service tme	(0.08229; 0.034773)	0%	(0.08229; 0.034773)	Normal
Failure type	(0.993556; 0.7134)	0%	(0.993556; 0.7134)	Normal

Outputs

Name	Equation
Number of failure	5.000+0.09Downtime-0.327Operating time+0.0072Service tme-2.00Failure type-0.00089Downtime*Operating time-0.000592Downtime*Service tme-0.047Downtime*Failure type+0.000318Operating time*Service tme +0.238Operating time*Failure type-0.01259Service tme*Failure type+0.0007Downtime*Service tme*Failure type
Through put	9516+513Downtime-843.6Operating time+643.6Operating time+30.84Service tme-2816Failure type-4.90Downtime*Operating time-2.334Downtime*Service tme-460Downtime*Failure type+0.668Operating time*Service tme+725Operating time*Failure type-48.46Service tme*Failure type+2.489Downtime*Service tme*Failure type

Next Steps

The Cpk is above the generally accepted value. You may be able to improve these results by repeating **Parameter Optimization** or **Sensitivity Analysis**.

If these results are unacceptable, you may want to reevaluate the design and the predictive models that describe the product.

Appendix 8: Model Summary

Statistical measure	Number of failures	Through put
N	50,000	50,000
Mean	1 3808	7,269
Standard deviation	2 0695	5,746.07
Minimum	-26.1694	-86,415.68
Median	1.4031	6.983.55
Maximum	25.7624	90,450.06

Model Assumption

Input name (X)	Distribution	Setting
Downtime	Normal	14.11;24.72
Operating time	Normal	12.57;6,686
Service time	Normal	138.9;134.6
Failure type	Normal	0.6786;0.4758

Statistical Summary

Statistical measure	Number of failures	Through put
N	50,000	50000
Mean	13808	7269.29
Standard deviation	20695	5746.07
Minimum	-26.1694	-86415.68
Median	1.431	6983.68
Maximum	257624	90,450

Optimization of the Input Means

Input X	Current	Low	High
Downtime	0.012952	0	30
Operating time	3.5885	0	12
Service time	0.08229	0	240
Failure type	0.993556	0	1

Simulated Results of the First Optimized Parameters

Output (Y)	Process performance	Percentage outside specifications
Through put	1.17	0.05%
Number of failures	2.98	0.00%

A Model Assumption

Input name (X)	New setting	Search range Low	High	Previous Setting
Downtime	0.012952;0.000341	0	30	0;000341
Operating time	3.5885;0.0589671	0	12	3.651;0.058671
Service time	0.08229;5.2052	0	240	0;5.2051
Failure type	0.9935556;0.7134	0	1	0.983397;0.7134

Values of Probability Measures for Maintenance Parameters

Measurement	Through put	No of failure	Service time	Operation time	Downtime	Failure time
Mean	5930	1.25	138.9	12.57	14.11	0.6786
Standard deviation	3031	1.506	134.6	6.686	24.72	0.4756
Number of runs	28	28	28	28	28	28
Ad	2.776	2.193	1.586	7.097	4.185	5.735
P-value	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005

Generated Model Summary for Dependent Variables

Measurand	Through put	Number of Failure
S	1302.66	1.35947
R^2	89.06%	51.72%
R^2(adj)	81.53%	18.53%
R^2(prod)	*	*

Optimum Dependent Variables for Maintenance Management in Tea Processing

Input name (X)	New setting	Search range		Previous Setting
		Low	High	
Downtime	(1.3334;0.000391)	0	5	(0.658288;000391)
Operating time	(9.9963;0.14972)	0	10	(9.9997;0.14972)
Service time	(2.5845;6.3553)	0	10	(1.7827;6.3553)
Failure type	(0.999806;0.7134)	0	1	(0.999033;0.7134)

SR575

ISO 9001:2019 Certified Institution

THESIS WRITING COURSE

PLAGIARISM AWARENESS CERTIFICATE

This certificate is awarded to

LANGAT JACKSON BIRIR

TEC/PGMT/04/15

In recognition for passing the University's plagiarism

Awareness test for Thesis **entitled**: **OPTIMIZATION OF MAINTENANCE PERFORMANCE MEASUREMENT OF CRITICAL MACHINES IN TEA PROCESSING: A CASE STUDY AT LITEIN TEA FACTORY** with similarity index of 6% and striving to maintain academic integrity.

Word count: 21443

Awarded by

Prof. Anne Syomwene Kisilu

CERM-ESA Project Leader Date: 19/10/2023