Addis Ababa University
Addis Ababa Institute of Technology
School of Mechanical & Industrial Engineering

Enhancement of Overall Equipment Effectiveness (OEE) through the use of Industry 4.0: In the case of Hilina Energy-Enriched Foods Manufacturing Industry

A Thesis Submitted to the School of Graduate Studies of Addis Ababa Institute of Technology, Addis Ababa University in partial fulfillment for the Degree of Master of Science in Industrial Engineering

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Declaration

I hereby declare that the work which is being presented in this thesis entitled "Enhancement of Overall Equipment Effectiveness (OEE) through the use of Industry 4.0: In the case of Hilina Enriched Foods Manufacturing Industry" is original work of my own, has not been presented for a degree of any other university and all the resource of materials used for this thesis have been duly acknowledged.

______________________	June 28 / 2023
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This is to certify that the above declaration made by the candidate is correct to the best of my knowledge.

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Abstract

Overall equipment effectiveness (OEE) is a metric used to measure machinery effectiveness while Industry 4.0 (I4.0) is a revolution of digital transformation which used to change convectional manufacturing industry to smart manufacturing industry, through its evolution always open for improvement of productivity, equipment effectiveness and efficiency of machinery, as well as create comfort zone for human and other habitats. This study aims to identify equipment effectiveness metrics and possible solutions for enhancing OEE in the manufacturing industry, specifically in the case of the Hilina energy-enriched foods manufacturing industry. By utilizing a mixed-methods explanatory research approach that involves qualitative and quantitative data collection and analysis with the aid of advanced analytics techniques and recognize patterns trained with data, big data is used. The data analysis identifies the biggest losses occurring at auxiliary grand machines, especially the filler and packaging machines, resulting in a current actual OEE of only 33.46 percent. However, the remaining auxiliary machines have an OEE of 79.64 percent, giving an overall OEE of 68.34 percent. Consequently, the study advocates using I 4.0 technologies such as the Internet of Things (IoT), smart devices with sensors, machine learning, and vision to mitigate downtime, speed, and quality losses of auxiliary grand machines and provide solutions to these issues. Moreover, through the analysis of big data, the study provides maintenance strategies and machine setups that can help reduce unexpected failures, the largest losses in organizations. Thus, the use of I 4.0 technologies can enhance OEE in the manufacturing industry by providing possible solutions for each problem. It is noted that the OEE improved from 68.34% to 73.36%. This study concludes that by using the industry 4.0 in the organizations can effectively enhance the effectiveness of their equipment and achieve maximum effectiveness.

Key Word: Overall equipment effectiveness, Industry 4.0, Root cause analysis (RCA), Big-data, Six big losses

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Enhancement of Overall Equipment Effectiveness (OEE) through the use of Industry4.0: In the case of Hilina Enriched Foods Manufacturing Industry

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Acronym

Symbol	Meaning
6big losses	Equipment failure, setup & adjustment, idling & minor stops, reduced speed, process defect, and reduced yield
6S	Sorting, set order, shine, standardize, sustain + Safety
8waste	Transportation, inventory, motion, waiting, non-value adding processing, overproduction, waiting, unused talent
ABC	Always Better Control
AI	Artificial Intelligence
ANN	Artificial Neural Networks
AM	Autonomous maintenance
BDA	Big Data Analysis
BMP	Best Manufacturing Practices
CNC	Computerized Numerical Control
DES	Discrete event simulation
DL	Deep learning
DRI	Digital readiness index
FMEA	Failure mode effective analysis
GMCI	Global manufacturing competitiveness index
HVAC	Heat ventilation air conditioning control
HMI	Human machine interfaces
I4.0	Industry 4.0
IIoT	Industrial Internet of Things
IoT	Internet of Things
LM	Lean Maintenances
MB	Market Based
MD-DSS	Model driven decision support system
MES	Manufacturing execution system
ML	Machine learning
MV	Machine vision
MOST	Maynard's Operation Sequencing Technique

MP	Manufacturing practices
MRL	Manufacturing readiness level
OE	Operational Excellence
OEE	Overall Equipment Efficiency
ORE	Overall Resource Effectiveness
PFMEA	Process failure mode effective analysis
RCA	Root Cause Analysis
RF	Random Forest
SCADA	Supervisory control and data acquisition
SFAT	Smart factory assessment tools
SMED	Single minuet exchange die
TPM	Total productivity maintenance
UNICEF	United Nations Children's Fund
WFP	World food program
WWBLA	Why-Why because logical analysis

Chapter one

1 Introduction to research project

Overall equipment effectiveness (OEE) is a type of operational excellence system of measurement used to measure the overall effectiveness of equipment or machinery and plays an important role in achieving and sustaining effective operation in organizations (Sharma, 2019). Also, a lean manufacturing tool that measures the process of different machines and equipment as per world-class guidelines, which used to improve the performance of machines. OEE used to evaluate the effectiveness of these initiatives and identify areas for improvement, also measures an organization's ability to reach its working objectives on its equipment portion. It combines the measures of working performance, quality, and availability of machinery with mathematical representations of the working performance of an organization and analysis. OEE is an excellent indicator for tracking a company's performance and identifying opportunities for improvement. It provides a direct focus on improvement efforts in areas related to equipment efficiency and effectiveness (Singh S. a., 2022), (Mjimer, 2021). An effective instrument for increasing revenue, reducing expenses or waste, improving customer happiness, and generally promoting the effectiveness of machinery. OEE in productivity is defined as the quality of being effective (doing the right things) and efficient (doing things right) and is a gauge for the rate of production and output per unit input. Productivity and efficiency are often used synonymously (Tsarouhas P. , 2018). OEE increases variables that stand for availability, performance efficiency, and quality. It combines the technical sides of effective manufacturing and processing (Ondra, 2022), (Ayal, 2021), (Hansen, 2001), (Sivakumar, 2022).

The term "Industry 4.0" is used to discuss the fourth industrial revolution, which was used to transform industry. It represents a new wave of technological development and a hybrid of best practices. This transformation uses a variety of cutting-edge technologies, including cloud computer algorithms, connected technology, data analytics, and advanced materials (advanced robotics, advanced machine learning, cyber physical system (Santos B. P.-S., 2018). Utilizing industry 4.0 technologies like automation, data analytics, and connectivity to enhance OEE. These technologies have the ability to gather and analyze data on the functionality of the equipment, spot inefficiencies, and develop better tools to raise OEE. Industry 4.0, or best manufacturing practices (BMP), refers to the application of cutting-edge technologies and tools (Sipica, 2021).

Industry 4.0 is transforming the way manufacturing companies operate their businesses. Industry 4.0 is defined as the current trend of automation and data exchange in manufacturing technologies, including cyber-physical systems, the internet of things, and cloud computing (Kagermann, 2013). The integration of digital technologies such as the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI) has provided real-time data to optimize manufacturing processes and productivity. One significant measure of manufacturing efficiency is OEE, which is a performance metric that quantifies the efficiency of a production line by taking into account availability, performance, and quality. The application of Industry 4.0 technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, can help manufacturers achieve greater productivity, improve efficiency, and reduce costs (Rüßmann, 2015).

OEE has been widely used as a tool to improve manufacturing equipment effectiveness in the industry. However, its integration with Industry 4.0 has increasingly attracted the attention of many researchers and practitioners. The use of OEE is becoming more popular in Industry 4.0 due to the integration of digital technologies that allows for real-time monitoring and maintenance of equipment. Therefore, this research project aims to explore the use of OEE as a critical performance indicator for the industry 4.0 framework and vice-versal, and rationalize its importance in manufacturing companies.

The objective of this research is to enhancing OEE as a tool for using industry 4.0. The research explores the challenges that manufacturing companies face while realizing OEE, including barriers, lack of technical expertise, and high costs. Moreover, the study will investigate the measures companies can undertake to improve the acceptance and execution of the OEE tool in their manufacturing processes. Through this research project, we aim to provide manufacturers with a framework for using OEE in the Industry 4.0 context and offer recommendations for how to integrate it into their manufacturing processes to enhance productivity and efficiency. The study will provide new insights into how OEE can enhance in manufacturing companies using I4.0.

OEE has remained a useful metric over the years, but techniques for enhancing equipment performance have evolved. This metric was developed in the 1960s and is still one of the most popular ones in the manufacturing industry. It is derived from three factors: availability is uptime (actual available time) divided by planned availability time. That is, how much time the machine was in use as opposed to the total time it was planned to be used. Is that the machine is running or

not and how much time the machine was in use as opposed to the total time, it was planned to be used, performance is computed by dividing the actual product produced by the total product produced, and it displays part rate (flow rate for progression manufacturing as opposed to mass production). How often does the machine is run and quality indicates whether the machine is producing high-quality goods? by dividing excellent parts by total parts. Good-count components can be utilized or sold because they meet quality standards (Ahmad N. a., 2018).
In conclusion, OEE is measuring effectiveness of machinery. For example, the availability of machinery at any given time, desired quality, and performance are directly related to the production of major products that the company is expected to produce. typically, higher returns are associated with more efficient production and quality. The convergence of these areas is seen as a major strategic phenomenon driving the world of manufacturing today. And almost all of them are focused on increasing production quantity, quality, and reducing costs. To do this, cost reduction techniques such as OEE are at the forefront of the manufacturing industry.
OEE continues to be an increasingly significant figure. Over time, improvement strategies have evolved and changed. Modern manufacturers are guided by technological technologies. The transition from Industry 3.0 to Industry 4.0 and 5.0 efficiency has opened up new ways to monitor and manage machine health (Alccer Vtor and Cruz-Machado, 2019). As a result, manufacturers improve OEE and base their decisions on accurate information to improve overall performance in the following ways: enhancing of machine availability, performance by minimizing speed losses issues, and lowering waste and raising quality

In this regard, as improving OEE has both direct and indirect effects on overall effectiveness and efficiency, the focus is on the variables impacting productivity as well as methods of improving overall effectiveness and efficiency (Islam, 2022), (Díaz-Reza, 2022). In the small, medium, and large manufacturing industries, availability, performance effectiveness, and quality rate with improved OEE and productivity are the key elements and principles of industry 4.0 (Mahmoodi, 2022), (Cañas H. M.-M.-B., 2021). Finally, the ultimate goal of improved OEE in manufacturing operations is increasing performance by decreasing input and maximizing output, which is the objective of production (Nain, 2022), (Ho, 2022).

1.1 Background of research

In recent years, the manufacturing industry has witnessed a significant shift towards Industry 4.0 technologies, which are transforming traditional manufacturing processes through the integration of cyber-physical systems, the Internet of Things (IoT), and advanced analytics. The goal of this transformation is to boost productivity, efficiency, and downtime reduction, which will ultimately result in lower production costs and more profitability (Pereira, 2017). The manufacturing sector has long been plagued by a variety of problems, such as costly equipment downtime, protracted production cycles, and high maintenance costs. Industry 4.0 technology offers a cutting-edge tool for manufacturing organizations, which have had to deal with constant technological solutions. Measurement, maintenance, and monitoring of dependability, availability, durability, performance, and quality have all been crucial in determining a manufacturing line's effectiveness as determined by OEE (Herrmann, 2017).

In the late 1980s and early 1990s. During this time, the Society for Maintenance and Reliability Professionals was established (Ljungberg, 1998), (Nakajima, 1988). As with OEE, industry 4.0 in the manufacturing industry initially focused on productivity, availability, performance, and quality improvement. (Meca Vital, 2020), (Hahn, 2020). While today subside of operational excellence of the manufacturing businesses.

Nowadays, in an organization with mass customization, OEE displays its limitations in highly customized equipment performance, quality, and availability. On the other hand, industry 4.0, which would incorporate sophisticated equipment technologies into processes, emerged as another in smart and portable way. OEE and industry 4.0 are two critical concepts in the industrial scope that are attempted to be explained in this paper, along with how industry 4.0 might aid in improving OEE. Theoretically, the findings demonstrate that OEE parameters and principles won't die out; rather, they'll be enhanced by new technologies, i.e., industry 4.0, to achieve high equipment operational metrics in organizations. Initially, OEE was strongly linked to Total Productive Maintenance (TPM) and was used as a vague benchmark for receiving the TPM Prize simply for productivity, but today it is about overall equipment or machinery effectiveness (Puvanasvaran, AP and Yoong, SS and Tay, CC, 2017).

Sadly, the majority of manufacturing organizations simply use OEE for performance evaluation and do not use it as a pilot system to improve the manufacturing processes. The current study seeks to investigate the advantages of increasing OEE with Industry 4.0 integration and to provide manufacturing organizations with practical suggestions for integrating digital technology into existing equipment management operations. To provide useful and realistic improvements for the manufacturing sector, the research project makes use of literature reviews, data collecting on production devices, data analysis tools, and discus with an accountable person.

1.1.1 Case company selection and description

Based on the following idea, a case company was chosen for this study: In Ethiopia, malnutrition is a significant issue and one of the main contributors to infant death (EthiopianStatisticalAgency, 2019). Enriched food production can play a critical role in addressing this issue by meeting the nutritional needs of the population. However, the enriched food industry registered in ISO in Ethiopia is almost non-existent, and the existing company, Hilina energy-enriched food manufacturing industry, has not been able to meet the increasing demand for enriched food due to insufficient manufacturing capacity and equipment failure, leading to significant losses. Therefore, enhancing overall equipment effectiveness using Industry 4.0 technology has been identified as a critical pillar issue to address in the study. The aim of the study is to improve the manufacturing capacity of Hilina Enriched Food, which has been identified as an important player in saving and rehabilitating many malnourished children in Ethiopia and East Africa since 1998. By improving the production capacity of this company, it is possible to save several malnourished children from death.

Hilina Enriched Foods Pvt. Ltd. was established in 1998. In order to combat the lack of micronutrients that children and other sections of Ethiopian society suffer from malnutrition, they prepare different types of food by enriching the flour and other types of food made from grains that are easily available in the country. When the center was first established, it produced vitamin A-fortified iodized salt and sugar for use by UN agencies, NGOs, and the general public. A French company (Groupe Nutriset) was added as a joint owner in 2006 based on the sale of shares. The company learned about the Plumpy nut, also known as RUTF, from UNICEF. This French medicine is intended to treat severe acute malnutrition in young adults (SAM). A franchise agreement was created with Nutriset SAS, the company that produces Plumpy Nut. The Plumpy Nut facility was opened in 2007 by UNICEF's Executive Director.

Since then, Hilina Foods has expanded its production capacity to meet all local RUTF needs. Additionally, Hilina Foods has launched a product known as Plumpy Sup (RUSF) to treat mild malnutrition. Hilina is also offering fortified foods such as fortified peanut butter and egg powder. Today, Hilina has expanded significantly in size and capital and added cutting-edge technology (4th revolution) and the latest equipment; this is the main reason for its growth. In addition, Hilina has built an on-site food laboratory and a modern and comprehensive food manufacturing facility to monitor quality production while expanding its horizons. To fill the huge gap in the country's food production system, Hilina has opened the door for other children to focus on producing nutritious and therapeutic foods. Enterprise capacity, modernizing and changing technology, and using a quality-controlled laboratory are the company's continuous improvements. As shown in the table below (Table 2), which illustrates and supports this view, Hilina Foods produces about 300 MT per month to meet the demand in Ethiopia. It has created the capacity to produce.

Table 1.1 Hilina enriched food product capacity progress

Year	2007	2009	2011	2018	2022
Capacity (in Tons)	400	3000	5000	8000	8400

Product of Hilina enriched food manufacturing industry

Plumpy Nut, Plumpy Sup, and Plumpy Dembuchi. The Amharic name for Plumpy Nut is "Nefis Aden," which means "life saver." A ready-to-use food supplement for rehabilitating moderate malnutrition Plumpy field products are working wonders for children suffering from food shortages all over Ethiopia because this magical formula is what Hilina is proud of and what makes it stand out. In addition to standing up for the children of Ethiopia, 50% of the raw materials needed to produce these products are produced locally, which has many positive effects on the local economy.

1.2 Research problem

There are several common problems that are encountered in manufacturing organizations against to improve equipment effectiveness. These include underutilized equipment, high costs associated with maintenance and repair, a lack of standardization in work processes, inadequate communication among departments, difficulty tracking training, qualifications, and time management tasks. One of the major issues facing manufacturing organizations in terms of equipment effectiveness is having the right operations and procedures in place to ensure the highest quality of output and less downtime. Other challenges include proper resource management, rapidly modifying to meet client expectations, meeting production timelines, and managing costs (Ahmad, 2018), (Ayal, 2021), (Irawan, 2022).

Hilina energy-enriched foods manufacturing industry problems related to Industry 4.0 are the big data analysis system used by the company, the fact that most of the machines are edge, and the fact that digital recorders of today, such as tip track and microleakage, have little cognitive processing. This makes it difficult to know the work status of machines and the quality of products properly and accurately; that is, it creates its own effect on the OEE level.

According to production data, the company's production line has a capacity of 8,400 tons per year of Plumpy sup and nut or 50 sachets per minute while operating at peak efficiency, but the company only produced 6,991 tons between January and December 2022, indicating poor efficiency. The auxiliary grand machines are responsible for most losses, with an average effectiveness for the line 14-hour average operation time instead of the expected 23 hours, which is the company has an average working efficiency is of 60.87percent (including filler and packaging machines) and fails to meet the expected line efficiency. According to this, the company is ineffective since the plan is much less than the actual (Rana, 2022). The production line at the company is not operating at peak efficiency and is failing to meet its expected capacity. The auxiliary grand machines seem to be responsible for most losses and are not operating at the expected 23 hours per day. Additionally, the company is producing less than its expected capacity, resulting in poor efficiency, the efficiency of the production line at the company and to propose solutions to improve the efficiency of the auxiliary grand machines.

In accordance with most losses' occurrence, the machinery status area on a daily basis is auxiliary machine or excluded filler and packaging machine. The machine's standard performance to run is 24 hours per day, but it runs 18 hours per day on average, while operating with a line efficiency the machine working operation in average. It also expects to reach at least good class company standard, which is 21 to 24hours per day. Currently, the company was found to have a daily average working performance level for auxiliary grand machines, including filler and packaging machines, is below half percent, but excluding filler and packaging machines, the auxiliary machine efficiency is above half percent, according to calculations and analysis conducted over the days lying between January 2022 to and May 2023. According to an OEE benchmark, this performance level falls between typical and world-class categories (Koch, 2003) (i.e., 100% is perfect, 85% is world-class, 65% is good or typical, and 40% is a low score) (Nakajima, 1988), (Ahmad N. a., 2018), (Adabavazeh, 2022). It also fails to meet the expected line efficiency and encounters a non-uniform output value on most of its production days as observed from the last daily output value record of the human-machine interface (HMI) installed in the filler and packaging room.

The research problem aims to improve Hilina energy-enriched foods manufacturing industry OEE levels from the current level to a good-class level based on the company standard and, ideally, to a world-class level of near-zero-defect production. The research targets standardized production, reduced downtimes, uniform daily output, and identifying root causes of frequent minor stoppages and longer downtimes, speed, and quality losses using big data and root cause analysis tools. By addressing gaps in internal and external factors and prioritizing possible solutions for each problem, the study seeks to improve the performance rate, quality, and availability of the company's auxiliary grand machines.

1.43 Research objectives

1.3.1 General objectives

The general objective of this research is improving the overall equipment effectiveness in Hilina energy enriched food manufacturing industry through industry 4.0.

1.3.2 Specific objectives

- Identifying equipment effectiveness metrics for effective operation of auxiliary grand machines
- Investigating the current overall equipment effectiveness trend of auxiliary grand machines in Hilina's energy-enriched food manufacturing industry
- Developing a possible solution for auxiliary grand machines to enhance overall equipment effectiveness through the use of Industry 4.0 in the Hilina energy-enriched food manufacturing industry

1.4 Research question

- What are the equipment effectiveness metrics for the effective operation of auxiliary grand machines?
- What looks like the current application of the overall equipment effectiveness trend in auxiliary grand machines in the Hilina energy-enriched food manufacturing industry?
- What are the possible solutions for auxiliary grand machines to enhance overall equipment effectiveness through the use of Industry 4.0 in the Hilina energy-enriched food manufacturing industry?

1.5 Methodology

In this heading, the research topic, methods, and important techniques are briefly and clearly discussed and summarized. It emphasizes how important it is to take academic viewpoints and big data into account when addressing the lack of the best manufacturing equipment effectiveness system of measurement approach in the manufacturing industry of Hilina enriched food manufacturing industry. Additionally, it highlights the importance of using industry 4.0 or the fourth industrial revolution, as a crucial foundation for attaining the study's goals. The outline lists the steps that will be taken in the research to get answers to the research questions.

1.6 Outline of research

This paper is organized into five chapters. The research process for exploring the topic of how industry 4.0 has enhanced OEE in manufacturing industrial involves several key steps.

Firstly, it is important to provide a clear definition of key terms such as OEE and industry 4.0 to ensure that all participants have a shared understanding of these concepts. Next, a literature review should be conducted to assess the current state of knowledge on the subject, including any research gaps that need to be addressed.

Once these steps have been completed, the research methodology can be designed, outlining the approach, methodology, and big data collection techniques and their analysis that will be used to answer the research question. In this case, it may involve the collection of primary data from manufacturing companies that have instigated industry 4.0 practices to enhance their OEE performance. The big data can be gathered through various means, such as logbooks, sensors, machinery, operation, and production.

After the data has been collected, the information should be analyzed using statistical and analytical techniques to determine whether industry 4.0 has had a positive impact on OEE and whether it has reduced big loss indicators in the manufacturing sector.

Finally, based on the analysis conducted, conclusions should be drawn on the use of industry 4.0 in enhancing OEE in manufacturing industries, along with recommendations for future studies and for manufacturers who intend to use industry 4.0 practices to improve their OEE performance.

Overall, this research process is essential for understanding how Industry 4.0 can be used to improve OEE in manufacturing, leading to greater effectiveness in equipment and productivity in manufacturing operations.

1.7 Delimitation of scope and key assumption

1.7.1 Scope

The scope of enhancing overall equipment effectiveness (OEE) through the use of industry 4.0 included a wide range of activities such as identifying equipment effectiveness metrics and their berries of current equipment operational processes against good-class company standard levels such as performance indicators, benchmarking against industry standards and best practices, and assessing the relevance of industry 4.0 technologies and methods to initiate the industry. 4.0 skills and solutions, identify equipment working effectiveness tools, availability, quality, and performance-enhancing initiatives, lean manufacturing tools typically total productivity maintenance, repetitive trends and problems for typical regular patterns, and its solution to analyzing the results. Moreover, it includes assessing the current privacy controls of the industry 4.0 platform, investigating analytics to monitor performance, identifying areas for improvement, identifying current working processes and their performance indicators. It also includes developing tactics and plans to organize skills and solutions, conducting user exercises, managing the change process, ensuring user acceptance, and monitoring and recommending key performance approaches and its possible solution.

1.7.2 Limitation

The limitations of using industry 4.0 to improve OEE include high costs, a lack of standardization, data privacy and security concerns, the need for a skilled workforce, the complexity of data analysis and interpretation, the potential for data integrity issues, and the difficulty of integrating new technologies and practices into existing systems. These factors make it difficult for small or financially constrained companies to contrivance industry 4.0 technologies, practices, and may require significant expertise and resources to analyze and interpret OEE data. These limitations are expressed below:

- High costs, which may not be feasible for small or financially constrained companies
- Lack of standardization makes it difficult to compare OEE across different industries
- Data privacy and security concerns
- Need for skilled workforce to activate and keep industry 4.0 technologies
- Difficulty in integrating new technologies and practices into existing systems.

1.8 Significance

This research is significant for organizations proactive in optimizing processes due to rapid technological advancements and a competitive global environment. OEE, a tactically effective management tool, is used to maximize profit and minimize waste. The research involves improving OEE to increase equipment effectiveness using Industry 4.0. OEE analysis provides a comprehensive view of the operational process and identifies areas for improvement. Additionally, it helps identify bottlenecks that can delay processes and improve overall equipment organization effectiveness. The research's results are beneficial to the manufacturing industry, like Hilina's enriched food manufacturing industry, by maximizing profit and minimizing waste through improved OEE performance measurement for effectiveness, considering both visible and hidden factors.

The study is also significant to groups such as Ethiopia by contributing to the economic development of industry as well as employees through improved technology metrics, culture, and skills; managers by providing information on how to improve effectiveness; researchers by serving as a reference for further study; and the organization itself by improving quality, reducing costs, increasing equipment effectiveness, improving process responsiveness, developing suitable solutions, and keeping the overall equipment effectiveness of machines.

Chapter two

2 Literature review

The literature review summarized the results of a thorough investigation of the literature on methods for increasing overall equipment effectiveness (OEE) in manufacturing companies. This was the first procedure for data collection in this study. The investigation focuses on enhancing OEE using Industry 4.0 in the manufacturing industry. Peer-reviewed academic journals that are published in English are the only sources for the target literature. Numerous published journal articles, internet sources, and books were studied in order to learn more about the concept and benefits of growing OEE in different manufacturing organizations. However, the most relevant research papers are first located and compiled utilizing keyword, title, and abstract searches across a number of online databases, including Google Scholar, the Emerald database, Springer, and IEEE. OEE, Industry 4.0, big data, downtime, and real-time analysis in the manufacturing industry are some of the keywords used. But various combinations of them were working to verify the scope of the search results.

There are numerous studies on this topic that are related to it, for instance:

- How operations are tilted toward industry analytics and engineering processes is examined and connected in Industry 4.0 to decrease waste.
- Next, learn how data analytics techniques are utilized to increase the OEE of CNC machines.
- One more explains how to conduct a thorough literature review and gives a theoretical overview of various approaches to overall equipment effectiveness.

Such and such other related articles, books, studies, and reports were found at this time on Google Scholar using keywords, titles, and abstracts. There are 31,200 hits, of which 12,023 are articles, of which 713 cover the last half-decade, from 2013 to 2023. However, only 31 journals are relevant, sorted, and presented. Those articles are presented in the second chapter, Section 2.2.1 (theoretical and systematic review), as relevant and as activities to improve OEE using Industry 4.0. The search was limited to the most recent articles in the databases for the last decade (2013–2023) to investigate the improvement of OEE. As a result, several methods, tools, and strategies to improve OEE have been discovered using a systematic literature review. On the other hand, many approaches reported by previous researchers have been reviewed and collected, which will be used to investigate the future development of OEE metrics.

The theoretical review of the literature is focused on understanding and critically evaluating existing relevance theories on the analysis of OEE and its fundamental views about the keywords, which includes an overview from different perspectives from the past to the present. A theory-driven approach that aims to identify key ideas and relationships, gaps in existing knowledge, and areas for further OEE research This study, included in a theoretical review of OEE, is typically based on secondary sources such as academic papers, books, and review papers that have a theoretical focus.

A feature selection approach is used to identify the most important factors related to the study, such as set-up, segmentation, and defective start-up. The scholars analyse the data and conclude that most outages are caused by different reasons and issues. A new, modern integrated OEE model is proposed using a best-selecting method. The scholars also cover the basic definition of OEE, differentiate between traditional and modern OEE, discuss basic factors of OEE, and analyse trends in OEE research. Finally, it reviews tools and techniques used to improve and analyse OEE and summarises gaps in the literature.

Many researchers are now considering how Industry 4.0 might improve OEE. With the help of maintenance, organizing, and problem-solving strategies, OEE provides a functioning logic based on six big losses and continuous process improvement. While industry 4.0 provides tools for optimization, control, monitoring, and autonomy (Rosin F. F., 2020). Therefore, the advancement of OEE is speed up by these technologies. The automation of inefficient operations, on the other hand, simply exacerbates and magnifies their ineffectiveness (Mayr, 2018). Thus, OEE Improvement has a favorable effect on automating operations with developing technology. The examined publications suggest that some OEE could benefit from industry 4.0 technologies. It does not cover every OEE or every premise. The immediate effects that these two tools have on consumer satisfaction may once again be what annoys consumers about effectiveness.

However, beyond theory or some theoretical frameworks, Industry 4.0 technologies' effects on these tools are minimal. A crucial component, such as an empirical and realistic study to confirm the true impact using, for instance, performance indicators for this measure, is missing. The impact on other OEE, like as TPM (total production maintenance), people, and teamwork, however, is less well researched. This can be the case because they have an internal impact to lower expenses for the business even when they have no direct impact on the client.

2.1 Theoretical overview of OEE

An integral part of a production line is the auxiliary grand machines. Reliable auxiliary machines are essential for the machinery to operate effectively and efficiently. Research on the usefulness of auxiliary grand machines has been conducted over the years. For the efficient operation of auxiliary grand machines, this literature review discusses equipment effectiveness criteria. The three equipment efficacy metrics now cited by the majority of academics are:

- Overall equipment effectiveness (OEE)
- Maintenance metric (MTBF, MTTR, and MDT)
- Total productive maintenance (TPM)

The Overall Equipment Effectiveness Efficiency is one metric for evaluating the performance of auxiliary machinery (OEE). OEE is a crucial technique for assessing how effectively various equipment operate in a manufacturing facility. Based on three criteria availability, performance, and quality it is used to assess an auxiliary machine's performance. OEE, in Subramanian's opinion, is an accurate way to gauge how effective an auxiliary machine is (Subramanian, 2015). It is also a crucial tool for figuring out what causes losses during the production process.

Another metric for measuring the effectiveness of auxiliary machines in the manufacturing plant is maintenance. This includes MTBF (mean time between failure), MTTR (mean time to repair), and MDT (mean down time). These metrics can only be used to estimate the average repair time and frequency of breakdowns for auxiliary equipment; however, OEE considers all equipment effectiveness criteria, not just those related to auxiliary machinery.

Furthermore, other studies have shown that the implementation of Total Productive Maintenance (TPM) can improve the effectiveness of auxiliary machines. The application of TPM has demonstrated a significant improvement in the efficiency of auxiliary machines in connection to production to end users, which is overall operational excellence, claim (Liyanage, 2015). To reach the objective of zero breakdowns, waste, and accidents, TPM calls for the cooperation of all employees in an organization. An essential component of a manufacturing facility is the efficiency of auxiliary equipment. The literature research identifies a number of indicators that can be used to gauge how well auxiliary equipment is working. OEE, maintenance metrics, and TPM have all been found to be efficient ways to gauge, evaluate, and raise machine productivity. These measurements offer crucial information about the auxiliary machines' condition, which is crucial for preserving their efficiency over time.

In order to respond to the initial research question posed by the study's first specific objective aim, several literature assessments and critiques were carried out. According to Section 1.5, the research goal appears to be related to determining equipment effectiveness measurements for the efficient operation of auxiliary grand machines.

OEE is a set of measures that focuses on how effectively a manufacturing operation is utilized. The results are stated in a generic form that allows comparison between manufacturing units in differing departments, organizations, machines, and industries.

OEE is
- A measurement that identifies equipment potential or performance
- Identifies and tracks loss
- Identifies openings of opportunity & improving

Main objective
- Increase productivity effectivness
- Decrease cost and waste
- Increase awareness of the need of machine productivity
- Increase equipment life (MTTR. MDT, and MTBF)

Results of objectives
- Optimization profits and minimalization loss
- Attain (or maintain) a competitive edge

Figure 2.1 Definition, objective and result of OEE as literature perspective

OEE measures how effectively capital equipment is used by identifying constraints and how the constraints impact the OEE. The effectiveness is measured by multiplying availability and performance efficiency by the rate at which quality products are produced (Haddad, 2021). The actual calculations are

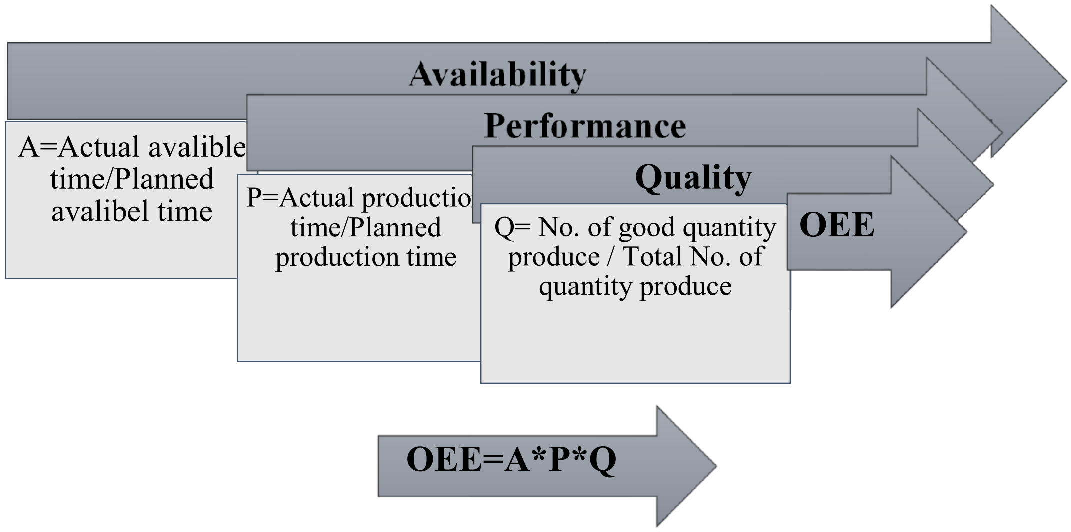


Figure 2.2 OEE formula in sequential type

Overall Equipment Effectiveness (OEE) is a widely used metric to evaluate the performance of manufacturing equipment. According to (Shin, 2018), OEE can be used to measure the productivity of a machine as it takes into account the availability, performance rate, and quality rate. The authors further suggested that the use of OEE be extended to other metrics such as maintenance metrics (Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF)) to further enhance the effectiveness of the evaluation of a machine's performance.

(López-Beltrán J. A., 2019) suggest that by focusing on improving each of these factors, manufacturing processes can be optimized to achieve higher OEE scores and greater efficiency. They also propose integrating lean tool methodologies into the improvement process to further enhance quality and reduce speed loss. The relationship between OEE and the three matrices of equipment effectiveness is a crucial aspect of measuring manufacturing efficiency and improving productivity. By focusing on availability, performance, and quality, organizations can optimize their manufacturing processes and increase their OEE scores.

2.1.1 Availability

Several studies have been conducted to investigate the factors that affect availability in manufacturing processes. One such study by (Kumar J. a., 2014) discovered that the biggest contributors to availability loss in a manufacturing plant were setup times, equipment malfunctions, and changeovers. The study added that lowering setup time and putting in place a preventive maintenance program could boost availability. Another study by (Sahu, 2019) studied how availability was affected by downtime in a pharmaceutical production facility. According to the study, unscheduled downtime caused by equipment failures and maintenance procedures had a big impact on availability. A computerized maintenance management system (CMMS) should be put in place to monitor and control maintenance activities, according to the study. Moreover, (Wang J. a., 2022) centered on enhancing availability in the production of semiconductors. The study suggested employing machine learning algorithms to detect probable equipment breakdowns in order to locate them before they happen. It was discovered that the strategy dramatically increased availability and decreased downtime. While, preventive maintenance programs, shorter setup times, and predictive maintenance techniques can all help to increase availability, a crucial component of OEE. Accessibility is the first consideration when assessing an item of equipment's overall performance. The availability team includes management, the production team, and the maintenance team. Review the attachment's availability calculation formula and make sure you understand each availability phrase completely.

Time that has been set aside for scheduled activities. The management of any organization is permitted to do this. In any organization that calculates OEE shift-wise, typically take into account minutes as the total available time for every shift. The management intends to provide a minute refreshment break and a minute lunch break per shift (Chandra, 2018).

$$\text{Availability} = \frac{\text{Actual available time}}{\text{Planned available time}} = \frac{\text{Run time}}{\text{Planned working time}} \ldots\ldots (\text{equ } 2.1)$$

$$\begin{aligned} \text{Planned available time} &= \text{Total time per shift} - \text{break time(lunch} + \text{refereshment)} \\ &= \text{Planned working time} \ldots\ldots\ldots\ldots..\ldots. (\text{equ } 2.2) \end{aligned}$$

$$\begin{aligned} &\text{Actual available time} \\ &\quad = \text{planned available time} - \text{planned downtime} - \text{unplanned downtime} \\ &\quad = \text{Run time} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (\text{equ } 2.3) \end{aligned}$$

Actual availability time denotes when the unit is actually ready for use without any additional interruptions, like planned down time (changeover time and set-up and adjustment time) and unplanned down time (machine breakdown and machine idle as a result of machine parts unavailability). Simply put, the machine is ready to produce products and is available.

2.1.2 Performance

According to the article, the relevance of the performance stage of OEE calculation, which is influenced by the production department, has increased in the context of Industry 4.0. (Gaiardelli, 2019) In particular, it is important to note how Industry 4.0 technologies, such as the Internet of Things (IoT) and sophisticated analytics, can be utilized to enhance the performance stage of OEE calculation by giving real-time data on worker and machine productivity. In order to locate bottlenecks and inefficiencies in the production process, IoT-enabled sensors, for instance, can offer data on machine speed, cycle time, and power usage the factory. Predictive models that can maximize machine performance and decrease downtime can then be created using advanced analytics approaches, such as machine learning algorithms. When it comes to the function of the production department, Industry 4.0 technology can boost labor force productivity by providing real-time monitoring of employee performance. Workers may benefit from wearable technology such as smart watches and eyewear.

$$\text{Performance } = \frac{\text{Actual Production Time}}{\text{Planned Production Time}} \dots\dots\dots (equ\ 2.4)$$

$$\text{Planned production time}$$
$$= \text{ Actual available time (means the machine is ready to produce products)} \dots (\text{equ } 2.5)$$

$$\text{Actual production time } = \text{ planned production time} - \text{ time loss due to minor stoppages} -$$
$$-\text{time loss due to the machine working at a slow speed} \dots\dots\dots\dots\dots\dots\dots (\text{equ } 2.6)$$

Actual production time means the machine is focused on only producing the product without loss of performance or machine-like minor stoppages due to a machine error or manpower issues. The machine has a slower cycle compared to its standard design. To enhance performance, focusing on the root cause of the speed loss on each operation of machine cycle is the priority. (Hassani I. E., 2019).

2.1.3 Quality

The third pillar of OEE is quality. Several publications, including Measuring Manufacturing Performance by Evaluating Overall Equipment Effectiveness (OEE) by, highlight the significance of the quality pillar of OEE and its link to the production department and the quality department. (Jadhav, 2018), (Gaiardelli, 2019) explain how the Internet of Things (IoT) and artificial intelligence (AI) are examples of Industry 4.0 technologies that can be leveraged to improve the quality pillar of OEE in the metalworking industry. IoT-enabled sensors can track the manufacturing process in real-time and provide information on variables like temperature, roughness, and vibration that may have an impact on the quality of the final product. After this data has been analyzed by AI systems, patterns and trends can be found that can be used to anticipate and stop product faults before they happen in in robotics factory. They underline the importance of the quality pillar in OEE and the necessity of efficient quality control in their essay to guarantee customer happiness. According to the authors, a variety of causes, including human mistake, environmental conditions, and mechanical problems, can result in product faults. They also go over how crucial it is to monitor defect rates and how to use statistical process control approaches to find the source of errors and fix them.

Concerning the role of the quality department and the production department, (Jadhav, 2018) imply that collaboration between the two departments is necessary to achieve product quality. The production department is in charge of making sure that the production process complies with these requirements, while the quality department is in charge of establishing quality standards and monitoring product quality. Additionally, the authors propose that methods like Six Sigma and Total Quality Management can be used to improve the quality pillar of OEE. Regarding the functions of the production department and the quality department. To help these departments operate together more effectively and efficiently, (Gaiardelli, 2019) suggested that Industry 4.0 technologies can enhance communication and collaboration between them. As a result of the ability to share data among departments, IoT-enabled sensors can collect data that gives departments a better understanding of the production process and enables them to identify and address quality issues more quickly. With real-time data monitoring and analysis, enhanced departmental communication and collaboration, and the application of AI and other cutting-edge analytics methods, the quality pillar of OEE will be improved.

Only two parameters that are simple to measure are used in the OEE calculation of quality. The good quantity produced comes first, and then the overall quantity produced over all shifts comes second.

$$\text{Quality } = \frac{\text{Total No. of good quantity produce}}{\text{Total No. of total quantity produced}} \ldots\ldots\ldots\ldots\ldots..(\text{equ } 2.7)$$

$$\begin{aligned}\text{No. of total quantity produced} \\ &= \text{No. of good quantity produce} \\ &+ \text{No. of bad quantity produced} \ldots\ldots(\text{equ } 2.8)\end{aligned}$$

$$\text{OEE} = \text{A} * \text{P} * \text{Q} \ldots\ldots\ldots\ldots\ldots..(\text{equ } 2.9)$$

Were A = availability, P = performance, and Q = quality

Availability – Machine or service running or not, Performance -How fast is ruining machine or service, Quality – How many products satisfied the requirement.

In summary, the quality pillar of OEE is essential for maintaining a high level of customer satisfaction, and effective quality control can reduce the number of defective products. Cooperation between the production department and the quality department is crucial for achieving improvements in product quality and increasing OEE (Adabavazeh, 2022).

2.1.4 Six big loss

The six big losses in equipment or machines are generally thought to result from three basic factors of OEE (Nakajima, 1988), (Vijayakumar, SR and Gajendran, S, 2014), (Tsarouhas P. , 2018). According to (Doračić, 2020), Breakdowns, setups and adjustments, idling and minor stops, speed losses, quality faults, and reduced yield are the six major losses in equipment or machines. These losses are connected to the three OEE aspects of availability, performance, and quality. Advanced technologies like the Internet of Things (IoT), big data, and artificial intelligence can be applied in the context of Industry 4.0 to solve these losses. In the moment information about machine operation, such as temperature, pressure, and vibration, can be obtained from IoT-enabled sensors in industry. The downtime caused by machine failures can be decreased by employing big data and artificial intelligence techniques to evaluate this data and forecast possible breakdowns before they happen. Additionally, data analysis can be utilized to pinpoint equipment failures that occur frequently and create preventative maintenance plans to minimize setup and modifications. The total weight of OEE depends on the total average wight of 3 basic matrices, since different losses within OEE weighted (Berzins, 2022), (Yuniawan, 2014), (Maran, 2012).

$$\text{Weighted Availability} = \frac{(A1 * W1) + (A2 * W2) + \ldots + (An * Wn)}{\text{Total weight}} \ldots. \text{(from equ 2.10)}$$

$$\text{Weighted Performance} = \frac{(P1 * W1) + (P2 * W2) + \ldots + (Pn * Wn)}{\text{Total weight}} \ldots \text{(from equ 2.11)}$$

$$\text{Weighted Quality} = \frac{(Q1 * W1) + (Q2 * W2) + \ldots + (Qn * Wn)}{\text{Total weight}} \ldots \ldots \ldots \text{(from equ 2.12)}$$

$$\begin{aligned}\text{OEE} &= \text{weighted averages of the Availability} * \text{weighted averages Performance} \\ &\quad * \text{weighted averages Quality} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \text{(from equ 2.13)}\end{aligned}$$

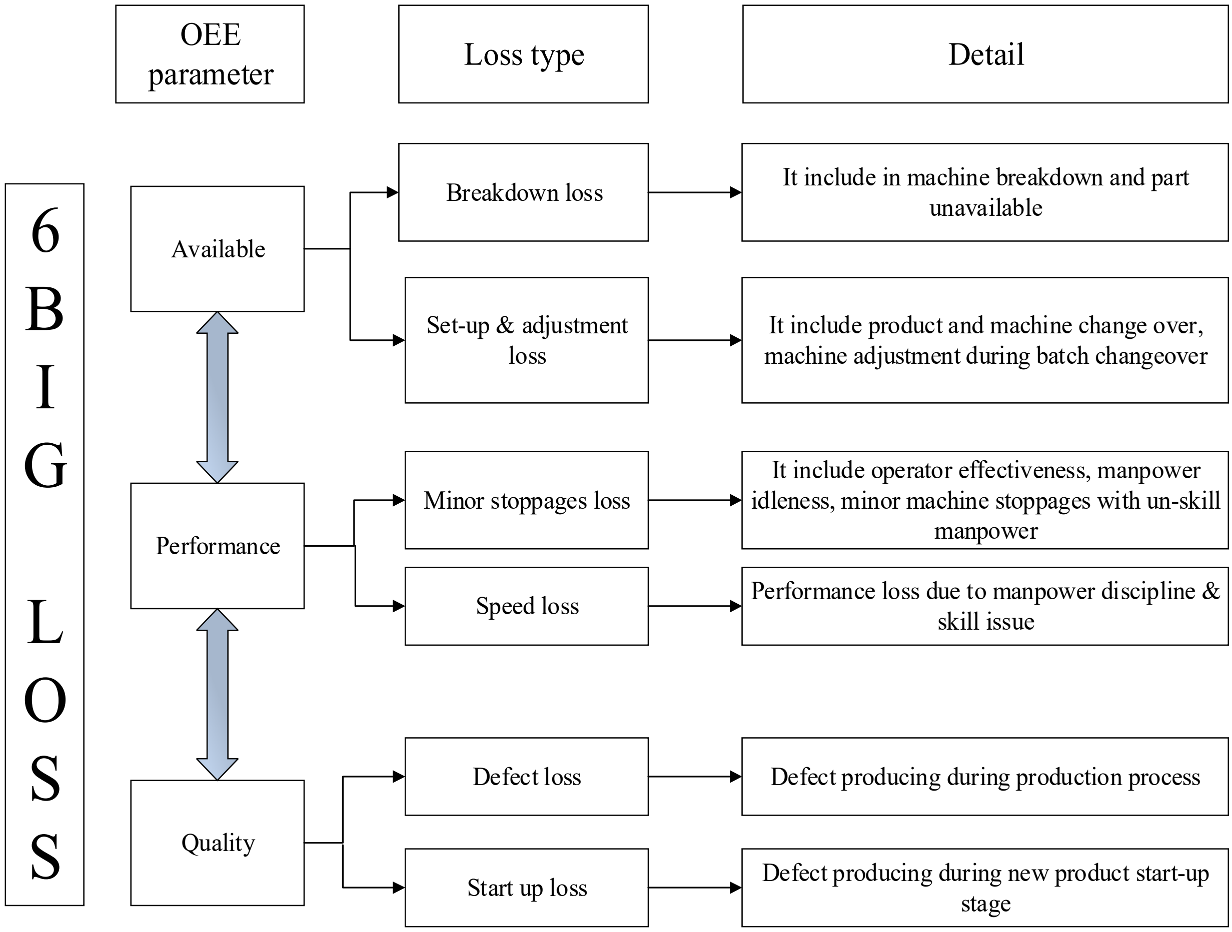


Figure 2.3 Six big losses of OEE

Overall Equipment Effectiveness (OEE) is an industry-standard measurement used by manufacturing companies to assess their production processes' efficiency. OEE calculates the ratio of good products produced to the maximum possible output during a specific period. OEE comprises three basic metrics: availability, performance, and quality of equipment. Availability assesses the percentage of time that the equipment is running, and thus, available to produce. Performance considers the production rate of the equipment compared to its maximum production rate. Quality considers the percentage of the output that meets the desired quality standards. Regarding the world-class standard, an OEE score of 85 percent is generally accepted as world-class or best-in-class. To achieve a world-class OEE score, companies typically aim for an availability rate of at least 90 percent, a performance rate of at least 95 percent, and a quality rate of at least 99.9 percent (Jonsson, 1999), (Zuashkiani, 2011).

2.2 Empirical review

A systematic review is focused on identifying and summarizing all relevant empirical research on analyzing and improving OEE by using different methods in different machines for different industries, with special focus on the relevant tools used to improve it.

2.2.1 OEE in manufacture industry

2.2.1.1 Using lean manufacturing approach

Lean manufacturing is a systematic approach to reducing waste and improving efficiency in manufacturing processes. According to (Huang G. Q., 2018), lean manufacturing emphasizes continuous improvement, employee engagement, and a focus on value-added activities. The authors further suggested that the use of lean manufacturing can lead to significant improvements in manufacturing efficiency and quality. The scholars discuss how to improve the OEE of different machines in different manufacturing industries using lean manufacturing tools.

The lean manufacturing tool is very crucial because its fundamental point is to analyze loss during production activity, waste reduction, maximizing profit, capacity utilization, and improving OEE in different manufacturing industries, as described by different scholars in their studies. Lean tool expressed bellow (Fam, 2018), (Singh C. S., 2021).

Kaizen: for tiny improvements; single-minute exchanging die: for decreasing changeover; total productivity maintenance: for improved machine reliability; Poka-Yoke: for reducing defect errors; 6 S Methodology: for workplace arrangement: and 8 Waste: for process optimization.

- **Kaizen method & 6S**

On the way to Kaizen methodology OEE is improved by the application of Kaizen, and 6S is one of the pillars of lean tools: the improvement of the overall equipment efficiency (OEE) of a ring frame section of a textile processing factory through Kaizen. After applying kaizen, the major stoppage losses identified by pareto analysis were idling and slight stoppage, breakdown, yield loss, and reduced speed. The why-why-because logical analysis (WWBLA) work sheet was used to identify the root causes of the stoppage losses. From these perspectives, OEE was improved, productivity was improved, and the amount of defective goods produced decreased (Ahmad N. H., 2018).

- **SMED method**

Investigates the effect of applying the single minute exchange of die (SMED) technique as a lean manufacturing approach to reduce setup time and improve the OEE of an extrusion machine in a leading Palestinian aluminum and profiles company, resulting in an increase in OEE. By increasing OEE through practical actions, the company saved 218,400 USD per year (Haddad, 2021).

- **TPM method**

The application of total productive maintenance (TPM) in a manufacturing plant provides improvement. This technique for this company improved the OEE from 58.79% to 70.08% by using the OEE tool to calculate the OEE for the broaching machine. It demonstrates that although the factors of the OEE evaluated on the broaching machine are not reaching a world-class level, with continuous improvement, the performance of the machine was enhanced up to the level of world-class (Chandra, 2018).

- **Integrated lean tools**

The implementation of autonomous maintenance (AM) to improve the OEE of a computer numerical control (CNC) machine at an automotive component manufacturing line The process of AM application, which includes forming a team, TPM, 5S activities, 8waste, and Kaizen for continuous improvement, also discusses the OEE results before and after AM implementation. AM to improve the OEE of a CNC machine. The OEE value improved from 63.8% to 88.1% after the AM operation, surpassing the OEE world-class standard of 85% (Musa, 2015).

2.2.1.2 Using systematic analysis and reasoning approach

The scholars discuss how to improve the OEE of different machines in different manufacturing industries using a systematic analysis approach.

- **Change perspective tools**

The chicken bowl printing machine was analyzed using the theory of change perspective or ultimately reassessing, which is the failure-tags analysis, to identify the category factors causing engine failure, and the why-why analysis was used to identify the root cause of the problem. The theory of change was used to explain what should be implemented by the company to improve the OEE value (Irawan, 2022).

- **Decision making tools**

OEE to measure the productivity of a drum testing machine used to test tire performance in a tire company. It found that process failure mode effective analysis (PFMEA) and failure mode effective analysis (FMEA) effectively improved the OEE effectiveness for machines, with an average increase in the mean OEE from the analysis of material prepared according to the testing schedule. Machines were maintained with preventive and autonomous maintenance, operators received routine training, standard operational procedures, and procedures were reviewed periodically, the drum test room was maintained, and spare parts were provided (Sibarani, 2021). Besides choosing an appropriate maintenance plan, factors influencing maintenance effectiveness and its preventives include the use of proper techniques and tools for decision-making and the possibility of using artificial intelligent systems to support decision-making processes in the implementation of lean maintenance concepts with 6Sigma, which have the greatest impact on increasing the effectiveness of the enterprise. The rate of obtaining such information is essential because the OEE indicator values inform us on an ongoing basis about the productivity of the possessed machines (Antosz, 2020).

The simulation is used as a tool to measure production performance or usage under different operating environments using different types of variables. This paper provides a comprehensive overview of the use of data analytics in lean manufacturing tools to improve the efficiency of production processes. The organizations with the decision to reduce waste by using discrete event simulation (DES) tools The simulation results are found to be in an acceptable range, with an accuracy of above 95%. The proposed model-driven decision support system (MD-DSS) framework is an effective supervision tool that enables decision makers to reach their predefined targets during the line-balancing production process (Abd Rahman, 2020).

- **Statical analysis tools**

The use of OEE to monitor and improve the efficiency of manufacturing processes in pharmaceutical industries collects data from a pharmaceutical production. Data was collected from the XL device and par-code scanner to identify reasons for low OEE. Fishbone and Pareto charts were used to prioritize the causes, and corrective actions were suggested and applied to solve the problem. The scholars used predictive analytics to identify potential problems before they occurred and data-driven decision-making to identify the root cause of any problems. There were many problems that caused declines in OEE, like the use of inefficient production parameters. By applying some remedial measures, losses were decreased and OEE was improved (Theeb, 2016).

2.2.1.3 Using reducing time study and line utilization management

- **Critical path method (CPM) and the Maynard operation and sequence technique (MOST)**

The comprehensive analysis of the production process of an Indonesian pharmaceutical company shows low performance in the OEE metric. Through observation and analysis, the cleaning process of the filler machine was consuming a significant amount of time. To reduce the time, the critical path method (CPM) and the Maynard operation and sequence technique (MOST) were used. The result is in accordance with other MOST research results and other time-study method research results. The results showed that MOST is effective in reducing time and providing regular training to operators to use existing cleaning equipment properly. Adapted to the standard time and the division of tasks in parallel for both operators, it is expected that the time for the cleaning process can be faster and increase the value of OEE through increased availability (Omega, 2017).

- **Line utilization and management**

The application of OEE in feed processing enterprises to improve equipment effectiveness and productivity. It outlines the steps for applying OEE in feed processing and suggests a framework for improving the efficiency of equipment and production line utilization and management. It also outlines the importance of decomposing OEE indicators and data analysis to verify the reasons for low OEE. The authors propose and implement corrective actions to improve the OEE and use the overall equipment efficiency index system to monitor, evaluate, analyze, diagnose, and improve equipment and production lines (Jin, 2017).

An original OEE calculation for mainly serial production lines of serial, parallel, and combined machine systems in the production line from the knowledge of A, P, and Q of individual machines. The approach allows for a greater depth of machine efficiency analysis, which fulfills the approach of production based on decentralization. It also discusses the disadvantages of effectiveness indicators, such as not taking other relevant factors into account and the difficulty of finding all the necessary input data to calculate OEE. The methodology involves the calculation of the coefficients of availability, performance, and quality. Using five whys analysis technique to reduce speed loss, which is the most dominant loss among all types of OEE losses, Furthermore, it discusses the use of the total productivity maintenance measure of overall process effectiveness (OPE) to measure factory-level performance and perform factory-level diagnostics (Alevs, 2019).

2.2.1.4 Using Industry 4.0

Many current scholars are already thinking about how Industry 4.0 might increase production from all angles. OEE offers a working logic based on the six big losses and continuous process improvement with the aid of AI, maintenance, organizing, and problem-solving techniques. While tools for optimization, control, monitoring, and autonomy are provided by industry 4.0 (Rosin F. F., 2020). As a result, these technologies speed up the development of OEE. On the other hand, automating inefficient processes will only make them worse and more obvious. Therefore, increasing OEE has a positive impact on automating processes using new technology. For CNC machining production, a digital online OEE enhancement system was created using machine learning and data analytics, leading to improved OEE through real-time monitoring and machine performance assessment developed country (Yuan, 2021).

Big data analysis was also found to aid in reducing equipment failures and downtime, or big losses, further improving OEE (Munirathinam, 2014). A manufacturing industry that underwent a digital transformation that enhanced automation, data sharing, and other cutting-edge technology to develop smart operations. According to (Tayyab, 2019). Real-time monitoring and data analytics can be used to increase industrial efficiency and decrease errors. The authors went on to say that manufacturers may be able to enhance production processes and make data-driven decisions thanks to Industry 4.0. Manufacturers may increase productivity, increase efficiency, and cut costs by implementing Industry 4.0 technologies like the Internet of Things (IoT), artificial intelligence (AI), and big data analytics (Kagermann, 2013), (Rüßmann, 2015).

Numerous studies have examined the application of Industry 4.0 technologies in production settings and how well they improve Overall Equipment Effectiveness (OEE). A study by (Kagermann, 2013) demonstrates the significance of Industry 4.0 in converting conventional manufacturing systems into intelligent factories, leading to higher productivity and efficiency. Another study by (Kache, 2017) examines how big data analytics can be used to streamline production procedures and cut down on equipment downtime. Industry 4.0 is a digital transformation strategy that uses automation, cyber-physical systems, machine learning, big data, and the internet of things to increase industry production and efficiency. This technology is crucial for improving output and managing the industrial facility (Alcçer, 2019).

It places a focus on how modern technology is incorporated into processes, tools, and components. aims to transform the manufacturing organization from an unintegrated, unautomated, and inefficient one. It is also a smart factory that processes large amounts of unstructured heterogeneous data continuously in formats like video, audio, text, and others by utilizing artificial intelligence (AI), automation, cyber-physical systems, and IIoT. This helps to solve setup and adjustment losses in equipment effectiveness. Additionally, Industry 4.0 improves real-time decision-making and situational analysis by continuously giving real-time data, which raises the efficiency of machinery (Mourtzis, 2016).

- **Root Cause Analysis (RCA)**

RCA is a method of problem-solving that assists in locating the root cause of equipment-related issues and reduces their likelihood of recurring in the future. The goal of RCA's adoption of Industry 4.0 technology is to raise the industrial sector's Overall Equipment Effectiveness (OEE). According to a study by (Ahmed, 2022), (Alizadehsalehi, 2020), RCA in manufacturing industries can be improved by using Industry 4.0 technologies like the Internet of Things (IoT), Big Data Analytics, and Artificial Intelligence (AI). The study evaluates Industry 4.0's contribution to RCA and its capacity to boost OEE by rapidly locating and eliminating problem causes and preventing equipment breakdowns.

An increase in the effectiveness of the RCA techniques through the incorporation of Industry 4.0 is supported by the study conducted (Morgan, 2021) , (Gao, 2020). They look at how RCA is used in conjunction with Industry 4.0 technologies in the manufacturing of semiconductors and discover that an optimized RCA can cut average downtime by 55.8%. In addition, a study by (Vo, 2020) presents a hybrid RCA methodology that uses IoT and AI to help identify root causes more effectively and increase OEE. The study comes to the conclusion that this hybrid model can, over time, dramatically increase OEE, improve RCA effectiveness, and reduce equipment-related losses.

In the manufacturing sector, RCA is crucial for identifying and removing the root causes of equipment issues and improving OEE. IoT, big data analytics, and AI are examples of Industry 4.0 technologies that can be incorporated to improve OEE, minimize downtime, and maximize profits (Ahmad N. H., 2018), (Santos J. G., 2011). As a result, industrial sectors can benefit from industry 4.0 technologies by optimizing their Root Cause Analysis methodologies, which will raise OEE and the sector's total productivity.

- **Artificial intelligence**

According to (Sowmya, K and Chetan, N, 2016) measuring OEE in various manufacturing processes can be complex, and traditional methods may not provide accurate results. However, scholars have found that using artificial neural networks (ANN) can effectively measure OEE in these processes. ANN implementation allows for handling big data and is a simple tool for measuring the effectiveness of complex industrial processes, making it an effective method for assessing productivity in challenging production processes. Using machine learning and artificial intelligence to predict and increase productivity in the manufacturing sector Different machine learning algorithms, such as support vector machines, optimized support vector machines (using genetic algorithms), random forests, XG-Boost, and deep learning (pattern recognized trained with data), are implemented to predict the overall equipment effectiveness (OEE) value. In addition, using machine learning algorithms for the prediction of organizational KPIs using a real dataset from an automotive wiring company, the scholars demonstrate how precise prediction can be done using artificial intelligence techniques. The results show that deep learning and random forest with cross-validation have better reliability and performance (Hassani I. E., 2019).

Another integration of industry 4.0 and lean production to increase effectiveness and productivity in companies. The study identifies the tools of industry 4.0 used by companies, the reasons for their use, and the advantages of their use. The results show that IoT and Big-data are the most important tools integrated with lean production, allowing companies to improve their flexibility and productivity. The article also emphasizes the importance of integrating the human factor with the tools of Industry 4.0 (Gallo, 2021) .

Artificial Intelligence has become a game changer in the manufacturing industry, improving effectiveness, reducing waste, and increasing productivity. AI's application in manufacturing is predictive maintenance. Predictive maintenance uses machine learning algorithms to analyze data from sensors and predict when machines will require maintenance. This helps to reduce downtime and prevent costly repairs. Another example is quality control. AI-powered image recognition technology can identify defects in products during the manufacturing process, ensuring that only high-quality products reach consumers. This technology can also help reduce waste and improve customer satisfaction. A study by Accenture found that AI has the potential to increase labor productivity by up to 40% and reduce manufacturing waste by up to 25%. In conclusion, AI is revolutionizing the manufacturing industry by improving efficiency, reducing waste, and increasing productivity (Bhattacharyya, 2020).

The application of AI to improve manufacturing effectiveness The authors present a case study of a manufacturing unit and demonstrate how AI algorithms can improve OEE levels by detecting equipment failures, optimizing supply chain processes, and reducing breakdowns. The authors discuss various AI techniques, such as machine learning, pattern recognized trained with data, and fuzzy logic, and their applications in improving manufacturing levels. They also highlight the benefits and challenges of using AI in manufacturing (Phanindra, 2020).

- **Big-data**

Big data analytics improve OEE by collecting and analyzing large amounts of significant data from various sources to identify patterns and trends to improve equipment A, P, Q, and efficiency, predict equipment failures, and identify opportunities for maintenance and optimization, leading to increased uptime and productivity, ultimately driving growth (Mariani, 2022). An architectural framework for modeling the industry 4.0 solutions for big data-driven industrial processes use this as a basis. This uses manufacturing functions to demonstrate the applicability of the proposed framework. Preventive, corrective, and predictive maintenance, six big losses, and the other eight wastes are manufacturing functions that bother manufacturers more and more due to their high costs, safety issues, and complicated improvement.

Different analytical techniques for big data analysis exist, including machine learning, rough set theory, neural networks, and fuzzy logic (Hariri, 2019). The tenders of big data analysis in various fields, such as manufacturing, healthcare, fraud detection, and social applications It also includes several related big data analytics studies and discusses them. Future research should focus on the application of big data analytics to improve effectiveness in the manufacturing industry.

A key technology for enabling intelligent manufacturing and industrial systems is big data analytics (BDA). It refers to the procedure of gathering, reviewing, and analyzing enormous amounts of data in order to identify market trends, insights, and patterns that aid in the improvement of OEE and more informed manufacturing decisions. Companies rapidly and effectively design plans to sustain their competitive advantage because of the quick and efficient availability of this information (Wang J. a., 2022), (Shi, 2022).

This provides an overview of the vulnerability of big data and the various methodologies applied in this area, including the use of neural networks and rough set theory. The review of different studies found that the hottest topic is security and the neural network, while rough set theory is almost saturated. The study provides a picture of the overall development of big data in various fields and its scope for research (Wang J. a., 2022).

Many scholas, observe the way of collecting big data or analysing big data there are so many challenges, which related to missing data and recognize pattern in data. The challenges are solved on the following tools:

- **Deep learning (DL) machine learning type**

A form of machine learning known as "deep learning (pattern recognized trained with data pattern recognized trained with data)" uses trained artificial neural networks to find patterns in data. It is used to anticipate OEE and for various applications, including image, voice, and natural language processing. Collected big data from a semiconductor factory and used a deep learning (pattern recognized trained with data) model to predict OEE. The study found that the proposed deep learning model outperformed traditional machine learning models in terms of accuracy and efficiency (Chang, 2020). Deep learning is a subset of machine learning that uses artificial neural networks to learn from large amounts of data. One area where deep learning has been applied in the manufacturing industry is monitoring. Deep learning algorithms can be trained to analyze big data from sensors and other sources to monitor and improve OEE.

In a study by (Wu, 2019), a deep learning-based (pattern recognized trained with data) approach was used to predict OEE in a semiconductor manufacturing process. The researchers used data from sensors, production logs, and maintenance records to train a deep neural network. The network was able to accurately predict OEE, and the results showed that the deep learning approach outperformed other traditional methods.

Another study by (Liu, 2019) applied deep learning (pattern recognized trained with data) to predict OEE in a steel manufacturing process. The researchers used a convolutional neural network to analyze data from sensors and production logs. The results showed that the deep learning approach was able to accurately predict OEE and identify the most significant factors affecting it. Deep learning-based predictive maintenance for improving overall equipment effectiveness in the semiconductor manufacturing industry by (Kim, 2020) used deep learning techniques to predict equipment failure in the semiconductor manufacturing industry. The authors collected big data from various sensors and systems and used deep learning models to predict equipment failure and improve OEE. The study found that the deep learning models outperformed traditional machine learning models in terms of accuracy and efficiency. The authors concluded that pattern recognized trained with data (deep learning-based) predictive maintenance can significantly improve OEE and reduce maintenance costs in the semiconductor manufacturing industry (Kim, 2020).

In conclusion, deep learning (pattern recognized trained with data) is a powerful tool for analyzing big data in the manufacturing industry, particularly in monitoring and improving OEE. The studies by (Wu, 2019) and (Liu, 2019) demonstrate the effectiveness of deep learning in predicting OEE and identifying factors that affect.

- **Random forest (RF) machine learning type**

Random forest is a form of machine learning technique that is used to handle missing data and satisfies all the requirements for managing missing data; therefore, it seems ideal to use RF for imputing data via the following methods from numerous decisions to obtain a single result:

- First drop data points with missing value (not recommended)
- Then fill in missing values with media, mean, and mode or for numerical or category value

In scientific settings, missing data is a common real-world issue. Missing data is a problem since many statistical studies demand full data sets. Due to this, researchers must decide whether to impute data or ignore missing values when doing statistical analyses that call for complete data. However, it would not be a prudent practice to simply ignore missing data, as this could result in the loss of important information and a reduction in the strength of inference (Enders, 2010). Imputing missing data in these circumstances is therefore a more logical and useful course of action. Although there are numerous statistical techniques for impute missing data, many of these struggles in high A, P, and Q and large-scale data scenarios, such as OEE, OTE, OE, and other high-throughput issues. Missing data techniques are frequently solely intended for continuous data (such as production and machine cycle time (Aittokallio, 2009), and when applied to mixed data (i.e., data with both nominal and categorical variables), their implementation frequently fails in difficult data environments (LiaoS, 2014).

(Singh S. N., 2019) used the random forest algorithm to predict Overall Equipment Effectiveness (OEE) in manufacturing industries. The authors collected big data from a manufacturing unit and used random forest to model the OEE of the unit. The study found that random forest outperformed other machine learning algorithms in terms of accuracy and efficiency.

Currently there are several different RF missing data algorithms

a) Original RF proximity algorithm
b) On-the-fly-imputation algorithms
c) Miss Forest, a method

This also applies to the original RF proximity method (Rhodes, 2023) that was incorporated into the random Forest R-package. The "on-the-fly imputation" techniques included in the random Survival Forest R-package are a different family of algorithms that enable data to be imputed while a survival tree is being grown (Choudhury, 2020). The random Forest SRC R-package, often known as RF-SRC, has combined these methods so that they can be used in a variety of contexts, including classification, regression, and others. Miss Forest, a recently published strategy in, is a third strategy (Hu, 2023). By rephrasing the problem of missing data as a prediction problem, Miss Forest adopts a different strategy. Values are imputed by regressing each variable individually against all other factors and then utilizing the fitted forest to forecast missing data for the dependent variable. Miss Forest has been demonstrated to perform better than popular techniques like k-nearest neighbors and parametric multivariate imputation using chained equations (Faisal, 2021). In this study, the authors proposed a random forest model based on big data to optimize the OEE of computer numerical control (CNC) machine tools like cluster and run chart representation.

The model was trained on a large dataset of real-time sensor data collected from the CNC machines and was able to accurately predict the OEE and identify the key factors affecting the machine's performance. The results showed that the proposed model outperformed traditional machine learning algorithms and provided valuable insights for improving the productivity and efficiency of the manufacturing process (C. Li, 2021). Also, another proposal proposes a random forest algorithm for predicting OEE in a big data environment. They apply the algorithm to a real-world manufacturing dataset and demonstrate its effectiveness in improving OEE prediction accuracy using chart representation (Xu, 2019).

2.2.2 General critiques of OEE improving approach

Industry 4.0 is a cutting-edge approach to production, equipment effectiveness, and use of digital tools and technology that automates and improves industrial operations. In order to build good factories that can function more efficiently than conventional manufacturing, it needs the integration of technologies such as big data, artificial intelligence (AI), cloud computing, and the internet of things (IoT). Manufacturing organizations can dramatically increase OEE by using Industry 4.0 by rapidly addressing equipment performance issues and improving their equipment effectiveness operation and production processes (Arden, 2021).

While the other methods mentioned before, such as the lean manufacturing approach, systematic analysis and reasoning approach, and reducing time study and line utilization management, can be effective in enhancing OEE, they are not as advanced as Industry 4.0 on big data analysis and quick possible solution (Sanghavi, 2019). The use of lean manufacturing techniques and systematic analysis and reasoning can help identify and address inefficiencies in the manufacturing process, while reducing time study and line utilization management focus on optimizing the production line (Albliwi, 2015), (Wang S. T., 2020). However, these methods may not be able to achieve the same level of optimization as Industry 4.0 (Tao, 2018).

Additionally, combining these techniques might not always be as successful as utilizing Industry 4.0 on its own. It may be expensive and time consume to combine multiple approaches, and it is ineffective to incorporate tools and technologies from other approaches. Instead, applying Industry 4.0 could provide a more thorough, repeatable success, sustained competitiveness, era-specific cure, and long-term cost-effective way to improve OEE.

In conclusion, while other methods such as the lean manufacturing approach, systematic analysis and reasoning approach, reducing time study, and line utilization management can be effective in improving OEE, Industry 4.0 offers a more advanced approach that can significantly optimize equipment effectiveness operation processes. Using a combination of the available methods may not be as effective as using Industry 4.0 alone, as Industry 4.0 offers comprehensive, sustainable competitiveness, not just in the short term but in its long-term cost-effective approach to enhancing OEE (Luo, 2018).

2.2.3 Empirical literature review summary

Generally, journals have been using OEE to increase productivity in the manufacturing industry. OEE is used in the manufacturing industry to increase productivity, improve equipment efficiency, and prevent big losses and unexpected equipment failures. It included different tools and techniques, such as decision-making, big data analysis systems, deep learning, random forest, artificial intelligence, lean manufacturing tools, six major losses' avoidance tactics, maintenance strategies, machine setting, and OEE formulation. These articles only consider output and efficiency when evaluating organization effectiveness, not equipment status.

Previous scholars considered improving productivity further. This was conducted on a company problem base and supported with the above-referenced literature reviews because factors in the above-referenced studies were also found to be factors in the Hilina energy-enriched food manufacturing industry. However, some limitations were found in the studies reviewed above, as most of the studies assessed the impact on its output, and the mismatching of product type, installed machinery or equipment capacity and type, measurement techniques, and tools with the product type and setting of Hilina's energy-enriched food manufacturing industry led to the need for further study.

2.3 Literature gap

In this study, the literature gap between different scholars shows that there is a lack of literature that studies barriers to increasing the effectiveness of the overall equipment in different products in different manufacturing industries. Specifically, this focuses on the case of the manufacturing industry. Currently, there is a lack of research on new technologies such as Industry 4.0 to increase the overall efficiency of equipment in the manufacturing industry, this study aims to solve the gap. These gaps in the latest scholars' study are expressed below.

Lack of research on the improvement of OEE in the manufacturing industry, lack of integration of OEE with industry 4.0 for improvement purpose, dealing with expected and unexpected six big losses and other hidden losses, economic crises, and non-implementation or improvement of lean updated practices in the manufacturing department of the manufacturing process—these issues are common in the food and beverage industry. Most of the previous studies, in view of the new composition of OEE targets based on different machines or tools in different arrangements and based on line utilization methods and techniques (which are based on an almost un-updated lean approach only), have argued that OEE improvement can only be achieved through the lean approach.

Lack of focus on the application of the lean approach (such as single-minute exchanges, poke-yoke, 8waste, and 6S) combined with decision-making methods in manufacturing industries and the analysis of the impact of the lean approach on other key metrics of performance are insufficient in big data utilization and analysis, which means particularly when it comes to employing decision-making methods, showing the possible solution, and analyzing the impact of lean on other key metrics of performance is insufficient. Potential challenges that may arise when improving and implementing OEE in manufacturing enterprises, unattainable cost savings, and the impact of OEE on the three metrics of manufacturing machinery have not been adequately addressed. It also does not discuss the benefit (profit) analysis of technology upgrades, the potential risks associated with implementation, or planned and unplanned maintenance to further improve the OEE value of TPM pillars such as breakdown, incident, and defect. And also, these studies do not use the latest algorithms to predict organizational KPIs and performance. Instead, these studies only discuss and emphasize the challenges and barriers that companies face in integrating industry 4.0 and lean manufacturing but do not address the challenges and barriers that companies may face in using Industry 4.0 to improve OEE.

The last literature gap in this study, in the most recent and oldest studies, has shown that the collected big data is used to mainly identify root causes in a qualitative manner instead of showing the trend of each machine in quantitative ways. The reason is that these scholars mainly focused their study on measuring machine performance based on only production rather than machine status in different manufacturing industries. This is not showing effective and accurate results on machine or equipment availability, performance, and quality every time, which leads to six big losses and other machine-hidden losses.

These gaps can have significant implications for manufacturing industries, as they suggest that the current methods of collecting and analyzing big data may not be sufficient to accurately identify the root causes of problems and improve performance by using possible solution. Instead, there is a need to develop quantitative methods to analyze machine data, status, and performance, quality, availability in order to identify and address losses and improve overall machinery effectiveness.

2.4 Literature summary

The review covers various tools and techniques used to improve OEE, such as big data analysis, data collection and management, maintenance strategy, machine setting, possible solutions, and OEE analysis. In addition, we found that OEE is a process of continuously improving, streamlining, and standardizing an organization's OEE systems and practices to drive effectiveness, productivity, and quality throughout the organization.

This chapter also learns about the change and identifies gaps in the literature, such as the lack of research on the potential of new technologies and tools like Industry 4.0 to increase OEE in the enriched food manufacturing industry. The review concludes that OEE is a specific lean metric used to measure the performance of a manufacturing process on an output basis, while operational encompasses a broader range of factors and strategies on an output basis plus each machine's status at any given time. The scholars also provide examples of how OEE can be improved through tools like change of perspective, decision-making, and statistical analysis.

Finally, the review outlines steps for applying OEE in manufacturing and processing enterprises to improve equipment efficiency and productivity. Summarize the above literature in the precise way expressed below in Table 2.1.

Table 2.1 Literature review summary table

Author	Year	Method	Focus Area	Reason due to improve OEE
Adabavazeh, Nazila and Navabakhsh, Mehrzad and Amindoust, Atefeh	2022	SMED (single minuet exchange die) method integrated with lean production and 6sigma	Equipment	Cement product decrease
Irawan, Suhendi and Kurniawati, Chandra Ayu and Febiola, Sherly De		change perspective and ultimately reassess		Chicken bowl printing ability and keeping
Wang, Junliang and Xu, Chuqiao and Zhang, Jie and Zhong, Ray,	2022	Big data,	Manufacturing System	Poor manufacturing systems
Gallo, T., Cagnetti, C., Silvestri, C., & Ruggieri, A	2021	Big data (random forest) and IIoT	Equipment	Decrease efficiency and productivity in factories
Sibarani, Prince and Sofianti, Tanika D and Pratama, Aditya Tirta		PFMEA and FMEA		Loss company target of tire capability on highway
Singh, Sandeep and Khamba, Jaimal Singh and Singh, Davinder		Total Productive Maintenance (TPM), 5S, Kaizen, TQM (total quality management)		Uncontrollable production and loss of use of resources
Haddad, Tamer and Shaheen, Basheer W and Nemeth, Istvan		Single Minute Exchange of Die (SMED) (a lean manufacturing tool)		Increase overall production costs and operational time for aluminum products.
Rosin, F., Forget, P., Lamouri, S., & Pellerin, R	2020	Industry 4.0 (AI, maintenance, organizing, and problem-solving strategies)	Equipment	Productivity issues
Abd Rahman, MS and Mohamad, E and Abdul Rahman, AA		Discrete Event Simulation (DES)		Loss of competency in its product

Antosz, Katarzyna and Pasko, Lukasz and Gola, Arkadiusz		By artificial intelligence with lean maintenance		Unordinary production in enterprises
Hassani, Ibtissam El and Mazgualdi, Choumicha El and Masrour, Tawfik	2019	AI and machine learning algorithms	Equipment	Automotive cable production keeps quality
Alevs, Zdenvek and PAvlu, Jindvrich and Legat, Vaclav and Movsna, Frantivsek and Jurvca, Vladimr		Production lines of series, parallel, and combined machine systems in the production line		Automotive cable production keeping quality
Tsarouhas, Panagiotis	2018	Statistical analysis of the failure and repair data of the line	Equipment	Productivity and quality issues in the factory
Ahmad, Nafis and Hossen, Jamal and Ali, Syed Mithun		Kaizen and 6S (lean manufacturing tools)		Ring frames are considered rope-like fiber issues.
Chandra, Arunesh and Chaturvedi, Yatender and Kumar, Ajay		Total Productive Maintenance (TPM) (Lean Manufacturing tool)		Productivity issues for current global competitive
Omega, Dousmaris and Andika, Aditya	2017	Using time studies (MOST and CPM),	Equipment	Cleaning operators for pharmaceutical companies
Puvanasvaran, AP, Yoong,SS, Tay,CC		MOST (Maynard operational sequence techniques) combined with RCA		Hide waste from production issues.
Jin, Nan and Wang, Hongying and Kong, Dandan and Chen, Xiao and Fang, Peng and Duan, Enze and Qi, Zhongxian		Line utilization and management		loss of productivity and benefit to the enterprise
Theeb, N and Nusairat, Asem and Lubani, Muhammed	2016	Statical analysis tools	Equipment	Productivity losses that occur within a pharmaceutical production plant
En-Nhaili, Ahmed and Meddaoui, Anwar and Bouami, Driss		TPM principles and lean maintenance		Issue one improvement action for the industrial system's effectiveness.

2.5 Conclusion

This chapter presents a review of overall equipment effectiveness (OEE) in the manufacturing industry. Generally, journals have been using OEE to increase productivity in the manufacturing industry. OEE is used in the manufacturing industry to increase productivity and prevent unexpected failures. It included different tools and techniques, such as decision-making, big data collection and management, six major losses' avoidance, maintenance strategy, machine setting, and OEE formulation. Only look at tools and equipment when evaluating productivity. So, previous studies should be considered to improve productivity further. This was conducted on a company problem base and supported with the above-referenced literature reviews because factors in the above-referenced studies were also found to be factors in the food manufacturing industry.

1) There is a lack of literature studying the potential of Industry 4.0 to enhance overall equipment effectiveness in the energy enriched food manufacturing industry.
2) OEE is used in the manufacturing industry to increase productivity and prevent unexpected failures. It included different tools and techniques, such as decision-making, pattern recognized trained with data, big data collection and management of random forest, six major losses' avoidance techniques like big data tool like pattern recognized trained with data, maintenance strategy, machine setting, and OEE formulation.
3) The literature gap between different scholars shows that there is a lack of literature that studies barriers to increasing the effectiveness of the overall equipment in different products in different manufacturing industries.
4) The lack of research on the improvement of OEE in the manufacturing industry, the lack of world-class standards, dealing with expected and unexpected big losses and other hidden losses, economic crises, and the non-implementation or improvement of lean updated practices in the manufacturing department of the manufacturing process—these issues are common in the manufacturing industry.

Chapter three

3 Research design, and methodology

3.1 Introduction

This chapter makes an attempt to present the research design and methodology used in this study. The general methods and tactics of the research framework are covered first. Both qualitative and quantitative methods are used to assess the big data that has been gathered from diverse sources. Primary and secondary data from organisations (observation, recorder, cloud, IIoT) and literature are the methods used for data collection and conducting the overall research (journals and reports). The statistical analysis tools (Minitab software, Optimal ML), Google Sheets or Microsoft Spreadsheet are utilised to analyse the big data for the manufacturing system processing in order to obtain the settled items.

3.2 Research design

This study used an explanatory research design because an explanatory research design is used in this study to determine and make declarations on how industry 4.0 improves OEE in the Hilina manufacturing industry, binding cause-effect root cause, and to understand the relationship between the use of industry 4.0 technologies or tool on OEE improvement in manufacturing processes by providing possible solution for each problem. The study aims to explain how the application of industry 4.0 technologies leads to increased efficiency and productivity in manufacturing and how this can be measured through OEE. By using an explanatory research design, the study can establish a cause-and-effect relationship between the use of industry 4.0 and the improvement of OEE, providing valuable insights into the potential benefits of these technologies for Hilina's energy-enriched food manufacturing industry. And the method is ultimately able to handle mixed types of missing data (random forest) in its big data operation by interlinking a cause-and-effect relationship between industry 4.0 and OEE, and develop possible solution using pattern recognized trained with data. The research design was selected as it is characterised by specifying the nature and direction of the relationships between variables being studied and explains why specific phenomena occur while enabling prediction of future occurrences.

This study's main goal is to provide answers to the research questions that are presented in the study first chapter under section 1.5. The research questions are related to cutting edge technologies and practices in the industrial sector and their potential impact on improving overall equipment effectiveness this count as best manufacturing practices. To conduct research on these questions, a mixed-methods research design is used. This could involve collecting information to gain a holistic understanding of the equipment's condition. For illustration, data can be collected to measure the impact of the overall equipment effectiveness by analysing data related to production and deploying industry 4.0 to attribute the different causes affecting OEE, such as through studies, equipment data gathering and analysis of performance metrics, or obtaining insights and opinions from experts, managers, employees, and other stakeholders or users about industry 4.0 technologies and practices to identify success factors, challenges, and opportunities related to their improvement. Some potential methods for collecting data could include interviews, observations, and machine logbook, smart device, and data room analysis. The use of case studies is also used to identify and investigate industry 4.0 practises utilised for enhanced overall equipment effectiveness in a given context. Overall, the research design should be personalised to Hilina energy-enriched food manufacturing organisation context investigated and the research question addressed.

In designing a study that addresses these questions, a mixed-methods approach is appropriate. This involves collecting both numerical and qualitative data to gain a deeper understanding the big data in pattern recognized trained with data of the impact of industry 4.0 technologies and practises on improving overall equipment effectiveness since OEE using industry 4.0 heavily depends on big data and machine learning (like pattern recognized trained with data, random forest). The following outlines a possible mixed-methods research design for the two research questions settled in the first chapter, section1.5.

3.2.1 The research design study components

3.2.1.1 Research approach

The research questions were addressed using a mixed-methods research strategy, which combines components of numerical and non-measurable research to provide a response. Additionally, because it incorporates the advantages of both methodologies, it helps paint an overall picture that is more complete than a personal numerical or qualitative investigation.

The study used combined methods of data gathering, which are both numerical and qualitative data collection methods, since the nature of improving or measuring factories in OEE requires big data, so data on OEE is essential. Quantitative research deals with statistics, while qualitative research deals with words and the qualitative nature of vendors. Following both data collection procedures is important for collecting different types of knowledge, as is the explanatory research design, which enables the collection of extensive information.

The research involves a systematic review of the present literature and an empirical study of the utilization of industry 4.0 viewpoints in manufacturing industries. The literature review step includes a compilation of different sources of information on data analysis as well as its application in the context of industry 4.0. This involves analyzing current manufacturing processes and identifying areas for improvement. The best manufacturing practices in Industry 4.0 should be realized and their impact on OEE measured and analyzed. Data is collected through various techniques like interrogating (interviews), recording, and observations. The overall step is like

a) Introduction:

- Identifying equipment effectiveness metrics for effective operation of auxiliary grand machines
- Conducting a thorough analysis of current processes and identifying areas for improvement
- Identify the nature of the operation process, focusing on the operation type and process
- Identify the technology and potential practises for productivity losses and equipment operation
- List the activities and resources needed for the manufacturing operation.

b) Collecting, organizing, and analysing data

- Collection and development of a data type and source

Collecting data from various sources such as production systems, machines, equipment, or technology (sensor, recorder, computer numerical control, display cabinmates, machine learning, and vision), technique and maintenance, SCADA, quality and research development, plant manager, data room, department documents, blue- and white-collar worker interviews, and machine logbooks.

- Data analysis: to identify trends and patterns that can inform decision-making

Analyzing the data using advanced analytics techniques, such as computer algorithm, mathematical analysis, machine learning with representative chartlike (cluster, run and pie chart). random forest, and pattern recognized trained with data are used to full filed the missing data and to convert the data in recognized pattern respectively. Improving OEE using industry 4.0 (best integrated techniques and practises):

- Industry 4.0 technologies and tools

- BMP-based maintenance planning, and correction
- Big data, from big data handling, missing data (random forest (RF))
- Recognize patterns in data (pattern recognized trained with data)

c) Conclusion:

- Benefits of using BMP for OEE analysis and improvement
- Encourage employees' participation in problem solving and identify problem
- Future direction of research and recommendation.

Identifying the impact of industry 4.0 technologies, such as automation and connectivity, on operations and identifying areas where these technologies can be further given possible solution and mitigated to improve performance continuously monitoring, evaluating, and adjusting the process to make sure the desired level of OEE is maintained.

d) References

3.2.1.3 The overall interpretation of research design

The overall interpretation of the research design procedures reveals the rationale behind the selection of the methods, how they interact and relate to one another, and how they will contribute to achieving the goals of the study. It takes into account the restrictions imposed by the research design and how these restrictions might affect the study's effectiveness and dependability. The discussion in the written portion of the study, such as the methods section or the discussion section, of the flowchart's interpretation, such as the justification for the design choices or the anticipated results of the investigation, Overall, the written section offers a more thorough description and interpretation of the research design, while the flowchart is a great tool for outlining the study design in a clear and simple manner. The research design, comprising the procedures necessary to achieve the purpose, the procedure for gathering data, and the techniques for analyzing that data, is represented graphically using a flowchart. The research design flow chart is shown in figure 3.1 below.

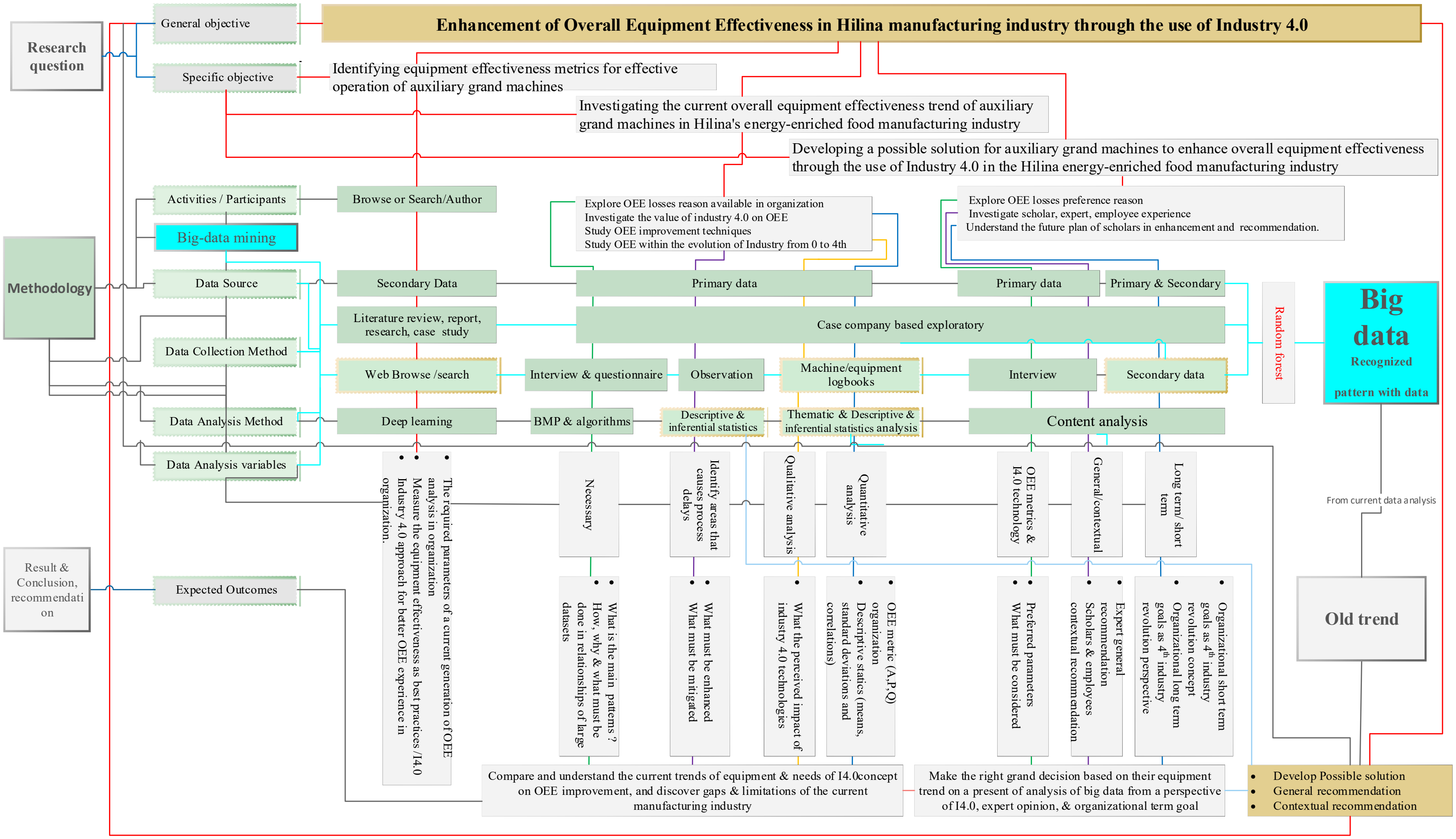


Figure 3.1 Research design

3.2.1.4 Research step

The specific acts or processes used to improve OEE using industry 4.0 are recognized as research steps, whereas the overall structure and plan for improving OEE using industry 4.0 are research designs. Research steps for the enhancement of OEE through the application of Industry 4.0 include data collection, analysis, change operation, and consequence identification. The study's entire methodology, including the choice of sample size and criteria, data collection instruments and sampling techniques, method of data analysis, and ethical issues, are all covered in the research design.

The research steps in the enhancement of OEE through the use of industry 4.0 are presented below:

- Define the manufacturing process and equipment to be analyzed.
- Identify relevant data to collect using various industry 4.0 technologies and other data sources such as sensors, HMIs, machines, employees, documents, observations, scholars, and reports.
- Collect and analyze data in real-time to diagnose inefficiencies and identify areas for improvement.
- Use strict analytics to predict future issues or identify opportunities to improve OEE based on current trends.
- Compare device changes such as process optimization, preventive maintenance, and equipment upgrades to enhance OEE.
- Monitoring the impact of the changes made through ongoing data collection and analysis and learning patterns and possible solution to determine the future

The research design on enhancement of OEE using Industry 4.0, on the other hand, covers the study's larger methodology, including the study's quantitative or qualitative nature, the sample size and criteria, the particular data collection methods, and the analytical strategy. In this study, planning carefully, paying attention to details, and having a firm grasp on the research question and objectives are all key components of research steps and research design. Both call for important ethical issues, such as getting study participants' informed consent.

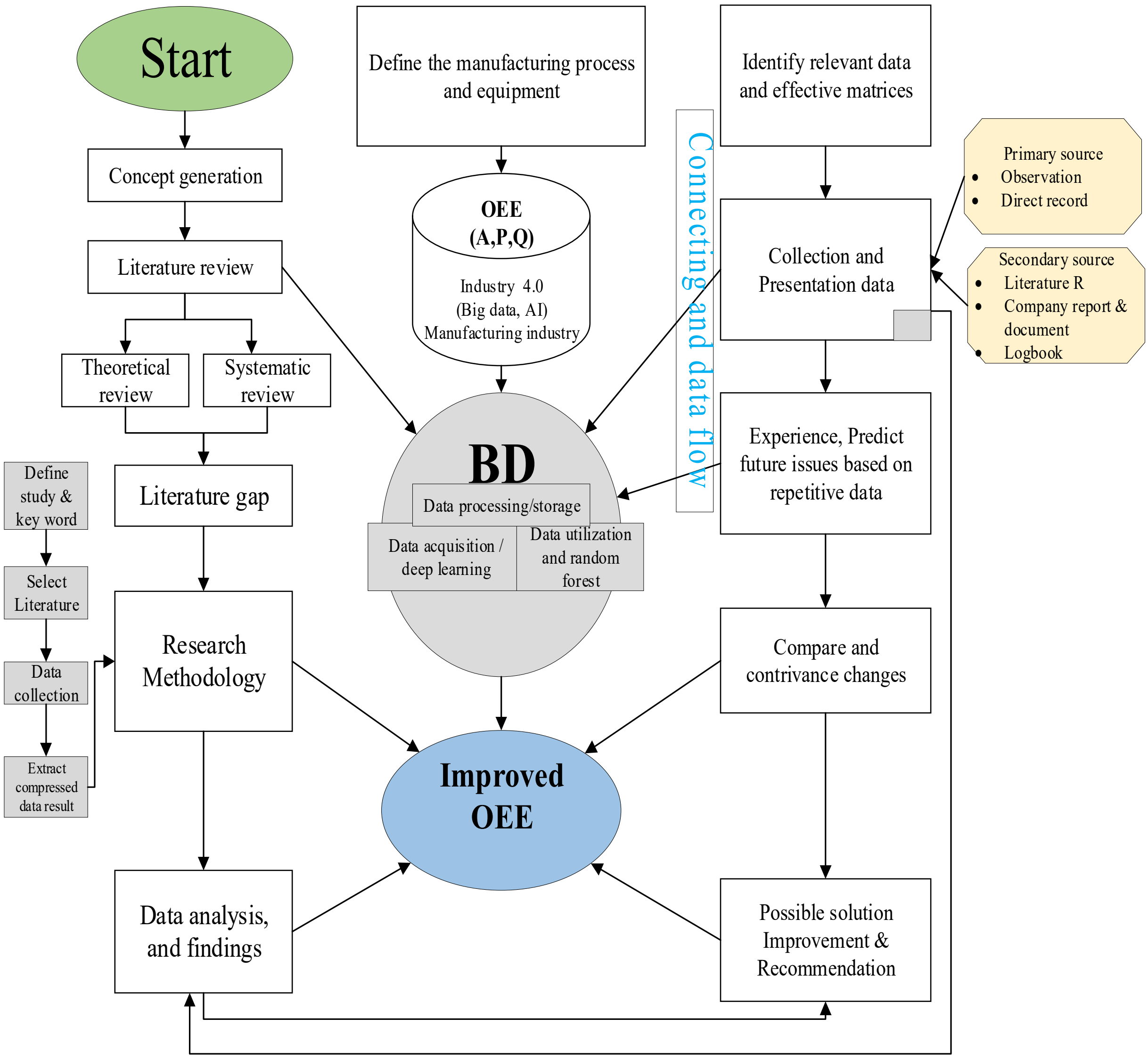


Figure 3.2 Research step

Research data

3.3 Sampling strategy & target population

Participants with expertise in industry 4.0 technology and practises were chosen using a purposive sampling technique in general. Purposive sampling is a non-probability sampling strategy where samples are chosen depending on the availability of data, transferring idea, the understanding of the inhabitants, and the goals of the study, like downtime, recursive problem, speed and quality loss information.

Also, this study used the following sampling techniques, depending on the research question, objective, and scope, to improve OEE using Industry 4.0 in Hilina energy-enriched food manufacturing industry. Because of the useful information taken by investigators working in the manufacturing industry, especially from the tools, general efficiency of the machines, and labor (blue- and white-collar workers), logbooks, smart device, expert opinion, technologies and tools. This includes individuals such as plant managers, management staff, chief, production supervisors, maintenance, quality technicians, and research and development managers, among others. Sample techniques in particular for selecting a sample from the data include simple random sampling (every unit in the data has an equal chance of being selected in the sample like working time, planned time, planned capacity, and planned product), stratified sampling (the big data is divided into subgroups and a random sample is taken from each subgroup; this is used for the data that is not homogeneous like auxiliary machine and filler and packaging machine or parallel and serious operation oriented machine), and stratified sampling to divide the data into groups called strata. Strata are grouped based on departments (production, RD, quality, technicians, and managers) within the Hilina-enriched food manufacturing industry. A sample is taken from each of these strata using the criteria set for screening, i.e., on the basis of how long they stayed in the company. The data for the analysis of operations using industry 4.0 technologies is the entire set of data that is collected from the manufacturing process. This could include data from all machines, production lines, equipment status and capacity, shifts, or even the entire factory. The target data for the study consists of operation, technicians, and production who are directly involved in securing the operational processes of the selected factory.

The target big data group consisted of operators, technicians, researchers, data encoders and analyzers, and managers who were directly involved in securing the effectiveness of the Hilina energy-enriched food manufacturing industry at Legetafo-Legedade because their general critique opinions were found to be essential to the study to create possible solutions for the problems. This data is chosen on the basis of how long they worked for the company (valid only if more than one year) and on the basis of their mandate to improve the effectiveness of the company. The total population of the Hilina energy-enriched food manufacturing industry is between two hundred and five hundred workers.

Depending on the available resources, the sample size should be adjusted accordingly. The study used the judgmental (selective) sampling method as it relied on the judgment of the investigation when choosing who to ask to participate. Thus, from the food industry of Hilina, an energy-enriched food manufacturing industry, the study was conducted on the Legetafo-Legedade, near

Addis Ababa, Ethiopia, manufacturing area. The sample frame of the study is eighty-one (seventy general workers plus seven technicians and five managers), but even if there is a population of seventy employees in the production room of Hilina energy-enriched food manufacturing industry, the study only included eight operators on the basis of their direct involvement in the effectiveness rate of the company and on the number of years they worked in the company. And of a total of seven technicians, only five were selected for the study as they met the criteria of working for more than a year. Again, of the four managers, only two were found to have a direct connection with operations. Hence, the sample size taken for the interview (formal and non-formal) is fourteen (a combination of eight operators, five technicians, and two managers working at different levels of the organization). Mainly the plant managers, department managers for techniques, maintenance, and quality, the RD manager, the production department, the data coordinator and analyzer, and other labor are used for the survey.

3.4 Data type & data source

The data type and source for improving OEE through utilizing Industry 4.0 is big data from various data generators and displayers of manufacturing processes. This big data was collected from the data sources of its type.

3.4.1 Data type

The data types used in this study varied for problem identification and to evaluate the impact of independent variables on the dependent variable. It includes quantitative and qualitative data types. These data include information on machine uptime, production output, downtime, breakdown, stoppage, idleness, operation cycle speed and cycle times, working hour, break time, number of shifts, number of workers, stopping and starting times, planned and unplanned downtime, machine uptime and equipment design status, and actual equipment status in the numerical data type, while speed losses, scrap, defects, concentrated, pure, quality, and trends in the qualitative data type on independent data variable, while, availability, performance, and quality is on side of dependent data variable.

3.4.2 Data source

In this study, these data types come from primary and secondary sources, such as PLC display, supervisory control and data acquisition (SCADA) systems (machine learning algorithm computers with a graphical user interface for a higher level of supervision of machines and processes), production department, research and development department, quality department, technique department, human resource department, networked data, experts, technical managers, researchers, machine logbooks, literature, documents about OEE and control systems, as well as IIoT devices, sensors, and smart manufacturing devices (like tip track, micro-leakage controller, and machine vision). These data sources are the sources of data in this study. Literature Review: different published journal articles, electronic sources and books were surveyed in order to understand the concept and benefit gained by improving productivity of a company.

Data in different formats was collected from the above-mentioned data sources, including digital, textual, symbolic, cards, charts, reports, descriptive, incidence, and non-occurrence of specific conditions.

3.4.2.1 Primary data collection method and its source

Primary data was obtained through continuous evaluation of the operational process in the study area, formal and informal contact with respondents and managers, and data collected in advance of the operational process, often through technology, direct observation, sensors, and IIoT devices (about efficiency, effectiveness of machines, and overall equipment's effectiveness constraints). Use this information to identify areas that cause process delays or reduce effectiveness, predict potential issues before they occur, and take corrective action to improve OEE. This has helped operators identify the root causes of problems or ineffectiveness and take proactive measures before they impact operations.

Industry 4.0 technologies, such as sensors, IIoT devices, and computer learning algorithms, have played a vital role in primary data by providing real-time data and insights into the manufacturing process to gain a better understanding of the process and identify ineffectiveness. For illustration, data collected from sensors and counter devices has been used to measure machine performance, downtime, and maintenance requirements to identify manufacturing ineffectiveness and improve overall equipment effectiveness. These were realized when making use of the following data collection methods:

a) frequency event and recording, using a combination of a stopwatch, counting machine, and sensor recorders.

Using cutting edge tool to increase overall equipment effectiveness measuring the frequency of an event involves counting the number of times it occurs in a given period of time. This is used to determine and monitor the frequency of equipment failures or maintenance requirements that affect OEE. Recorded machine downtime or maintenance downtime is used. Simultaneous machine and sensor recorders were used to record information about machine performance, running hours, quality statistics, and areas for improvement to increase the effectiveness of the equipment. So, by combining event frequency and recording techniques with technologies, manufacturers gain factory insights to improve OEE, reduce uptime, and optimize overall performance.

b) As event recording is best for actions with a distinct beginning and ending, it was used to record the occurrence and cause of downtime.

Event recording was used for features that have a distinct start and end, such as recording the events and causes of downtimes. Keeping records of the duration and frequency of events, identifying patterns and root causes, and taking corrective actions to optimize processes and improve OEE. Combining event recording with other tools, such as machine and sensor recorders, as well as applying technologies, will further increase the accuracy and effectiveness of downtime monitoring and analysis.

- A frequency measure was used to identify how frequently each cause of failure was occurring.

This was used to identify the most dominant or important problems and identify the necessary corrective measures. To do this analysis, we collected information on the problems and failures in the process and noted the frequency of each failure. Computer learning & vision, or display on IIoT devices were used to collect the data manually or automatically.

- Observation

Overall, by using industry 4.0 technologies and observation techniques, manufacturers gain valuable insight into their manufacturing processes, which improves OEE and ultimately leads to better results. By observing the manufacturing process, managers and operators identify areas that cause process delays or reduce effectiveness and take corrective action to improve OEE. However, machine learning algorithms have been used to analyze these large data sets generated by the manufacturing process and identify patterns or trends that human observers have missed. Direct observation is used to observe the process in a normal environment without changing that environment. Identified and observed the causes of some of the failures that resulted in delays.

- Formal and informal interviews, enquires

Both communication systems with operators, technicians, managers, and other staff were used to get information on the causes of failures, the observed downtimes in the operational process, and possible solution. The questions or interviews were used as part of gathering information from employees or supervisors contributing to improvement efforts. But more context was needed to determine their specific preferences regarding industry 4.0 and OEE improvement. mainly focus on the identification of equipment downtime, possible solution, and its impact on OEE.

Through papers, research, and expert interviews, a total of six significant losses were identified as relevant improvement concerns that directly affect OEE metrics in the manufacturing industry. Four chief, and one researcher were interviewed from different departments of the factory, including quality, data analysis, research and development, and maintenance (operator, mechanics, electrical, and production). The experts were selected based on their experience and willingness to participate. In addition, the correlation between waste, possible solution, and the many sources of waste in the organization was determined using the same method. All losses and waste are given to experts to identify the root cause of the problem. These are used to create real-time online decision-making that can be used to increase OEE and identify trends at the right time. By creating a digital transformation with distinct trends from big losses, reliable big data is generated to update OEE issues. It has also been said by experts that the 4th industrial revolution has boosted OEE in terms of technology.

The inquiry form aims at establishing factors affecting the OEE of Hilina energy-enriched food manufacturing industry. The study is designed to collect data that helps achieve the objectives of the study, especially for research question three. All information provided is treated with the utmost confidentiality and used purely for research purposes. Questionnaires were used as part of gathering information from employees, supervisors, and managers who could contribute to these improvement efforts, data analyzer but more context was needed to determine their specific use in relation to the combination of industry 4.0 and OEE improvement. Furthermore, the specific use of questionnaires and the questions asked depend on the particular goals of the OEE improvement effort, possible solution, and the specific context of the manufacturing operation. The questionnaire asks about the respondent's general characteristics, availability, performance, and quality of equipment, tools, and machine accessories.

3.4.2.2 Secondary data collection method and its source

Secondary data can be obtained from documents and records to calculate OEE values and identify the company's performance level. A literature review on secondary data sources involves surveying published journal articles, electronic sources, and books to understand the concept and benefits of improving OEE through utilizing industry 4.0. Documents and records were used as input for calculating the OEE value to identify the level of performance the company has reached. In addition to the literature review, other secondary data from the manufacturing sector was gathered and is relevant to the study. The following secondary data sources were used to improve OEE using Industry 4.0:

- Used real-time data on equipment performance and maintenance, as well as articles, studies, and reports that study overall equipment effectiveness, to identify areas for improvement and drive continuous improvement efforts.
- Reports from previous experiments or analyses, as well as current data sets, the technology and software necessary for real-time data collection and secondary data storage.
- Articles, research, and case study reports that provide best practices for improved OEE
- Research, articles, and studies from the manufacturing industry, industrial engineering management association (especially Toyota vehicle manufacturing company), and lean manufacturing tools to improve equipment efficiency and effectiveness, productivity, and quality, maximize profits, and reduce waste for the organization

3.5 Quantitative and qualitative data collection methods

3.5.1. Quantitative data collection method

Data on the overall effectiveness of equipment, the best manufacturing equipment operational processes, the acceptance and application of industry 4.0 technologies and practices gathered through studies. Utilizing industry 4.0 capabilities, quantitative data strategies for OEE improvement include real-time data gathering and analysis. These methods include sensors and machine-monitoring systems. A survey designed to gather data on various aspects related to industry 4.0 technologies and practices, possible solution, best manufacturing practices, and OEE. The survey was distributed both manually and electronically to allow for easy and quick data collection.

Time-series data collection techniques & data-driven methodologies are common.

3.5.2 Qualitative data collection method

More information about the perceived effects of industry 4.0 technologies and practices on overall equipment effectiveness by using non-numerical data such as observations, semi-structured interviews and interrogators, and surveys with participants who have experience with industry technologies and practices. The interviews were conducted in-person and remotely, depending on the participants' preferences and availability. These data are either directly or indirectly integrated with data obtained from quantitative methods.

3.6 Data collection procedures

Various methodologies are employed for this research process in order to accomplish the study objectives. Depending on the type and availability of data, both qualitative and quantitative data are collected. The information is gathered from Hilina energy enriched manufacturing industry. In order to increase OEE for category improving OEE, and best practices in light of the fourth industrial revolution, the survey's target demographic is the energy enriched food production industry. The steps to collect the data types from each data source:

- Identify the different data source for each data type, like below
  - PLCs display: the display to collect machine uptime, production output, downtime, breakdown, operation cycle speed and cycle times, stopping and starting times, planned and unplanned downtime, and actual equipment status in numerical data type.
  - SCADA systems: use the machine learning algorithm and graphical user interface to collect machine uptime, speed losses, downtime, breakdown, stoppage, operation cycle speed and cycle times, stopping and starting times, and actual equipment status in numerical data type.
  - Production department: collect data related to production output, expected and actual product quantitative data type.
  - Research & development department: collect data related to equipment design status, equipment status, and networked data in numerical data type.
  - Quality department: collect data related to quality scrap, defects, concentrated, pure, quality, and trends in the qualitative and quantitative data type.
  - Technique department: collect data related to trends, planned and unplanned downtime, breakdown in the quantitative data type.
  - Human resource department: collect data related to the number of workers, working hour, break time, number of shifts in the quantitative data type.
  - Experts and technical managers: collect data related to equipment status and maintenance issues in the qualitative and quantitative data type.
  - Machine logbooks in working area event happening in company related to maintenance, production, and other issues in the qualitative and quantitative data type.

- Researchers & development: collect data related to investigation, introduction, new issue, literature and documents and report about OEE and control systems in the qualitative and quantitative data type.
- IIoT devices, sensors, and smart manufacturing devices, tip track, micro-leakage controller, and machine vision: collect qualitative and quantitative data essential data in accurate and smart ways.

- Determine the data points we went to collect for each category and collect each data
- Enter the data into centralized database or software system. This used to organize and analyze the data more effectively by considering random forest machine learning type for full filling the missing data. And analyze the big data to identify trends and patterns by considering pattern recognized trained with data machine learning type. And developing recommendation to address OEE improving ways, monitor the data over time to tack the effectiveness of OEE improvement.

By following these steps, the required data types collected from each data source for analysis data.

3.7 Data summary

Table 3.1 Data summary table

Data		Data type	Data collection method	Data source (area)	Data collection procedure
Qualitative	Primary	Scrap, defects, concentrated, pure, speed & quality losses	Observations, participate	PLC display, networked data, technique department,	• Identify each data type and its source • Determine the data points we went to collect for each category and collect each data • Enter the data into centralized database or software system. • Analyze the big data to identify trends and patterns • Developing recommendation to address OEE improving ways • Monitor the data over time to tack the effectiveness of OEE improvement.
	Secondary	Scrap, defects, concentrated, pure, quality, breakdown reason, maintenance type.	Semi-structured interviews or questioners, and surveys with participants who have experience with industry technologies and practices	Production department, RD department, quality department, technical managers, expert, researchers, machine logbooks, documents, and smart manufacturing devices, technique department,	
Quantitative	Primary	Production output, breakdown, stoppage, working hour, break time, number of shifts, number of workers, stopping and starting times,	Observation, participate,	Out-put, quality, HR member, technical invitation, IIoT devices display, sensors, and smart manufacturing devices	
	Secondary	Machine uptime, downtime planned and unplanned operation cycle, equipment design status, and actual equipment status, speed and cycle times, breakdown reputation	Real-time data gathering through sensors and machine-monitoring systems, survey both manually and electronically, machine logbooks, daily monthly yearly report	SCADA, production department, RD department, quality department, technical managers, expert, researchers, machine logbooks, literature, documents, IIoT devices, sensors, and smart manufacturing devices, technique department,	

3.8 Validity and reliability

As the reliability of a research instrument is the extent to which the instrument yields the same results over multiple trials, the questionnaire used in the study can be considered reliable. And again, the fact that the data for the duration of downtime was recorded using a stopwatch, smart device, sensor, or data signal shows the reliability of the data, and check again and again, both manually and using computer algorithms with cross-check mechanisms. This can be proven by the standard deviation values obtained as a result of the closeness of the responses given.

- by varying respondents
- by taking into account the characteristics of the study and choosing appropriate methodology, by selecting the most suitable sample method (strata sampling or grouping the data)
- by ensuring respondents are not pressured in any way to select specific choices among the answer sets and to give their responses,
- by having people who understand the topic check if the survey has captured the topic under investigation effectively
- by getting the form checked for double, confusing, and leading questions
- by analyzing again and again, it has been proven that the instrument measures what it is designed to measure, which in turn implies that it is valid
- by checking same data in different source and type

The validity and reliability of the data were checked in this study to ensure the study's confidence by using the following steps:

- Appropriate, already-existing measures and common approach

This tactic aids in ensuring the reliability and validity of the assessment. Utilizing already-existing metrics and questionnaires to improve OEE via industry 4.0 is an efficient way to obtain important information and insights on the subject. Utilizing well-established frameworks and methods guarantees that the study is based on industry best practices and current norms. Making sure that the data is reliable and similar to results from other studies is a key step in ensuring that the conclusions and judgments are accurate. Additionally, using established measures and inquiry form saves time, resources, and equipment compared to developing new ones from scratch.

If there are any problems with the study's data on OEE, answer options, or layout, it entails testing the study on a small sample of respondents. Before distributing the question to a larger sample of participants in the OEE study, this was used to measure the survey's viability, reliability, and validity. This improved the study's findings' precision and generalizability.

3.9 Data analysis

3.9.1 Quantitative data analysis method

Descriptive & inferential statistics

The survey data was analyzed using descriptive and inferential statistics in order to understand the current state of OEE and spot prospective areas where OEE could be improved with the help of industry 4.0 technology. Key elements of the study data, such as the average OEE and the variability in OEE across various production processes, are summarized using descriptive statistics, such as means, and ordering data. This is used to identify specific areas of strength or weakness and to plan effective manufacturing process and fulfilling missing data. Willfully, inferential statistics are working to derive generalizable findings from the data that apply to a larger, heterogeneous source. For instance, it is possible to evaluate if certain data have a statistically significant impact on OEE or to find the elements most strongly related to high OEE rates using inferential statistics. These statistical approaches to analyzing study data used specialist application software tools (Minitab, Google sheets or spread sheet) to carry out the required calculations and process relevant reports and visualizations.

3.9.2 Qualitative data analysis method

Thematic analysis is used to analyze the qualitative data nature type. The analysis is used to distinguish and analyze patterns, themes, and other meaningful insights that arise from the qualitative data collection source (observations, semi-structured interviews or question, and surveys) on improving OEE using industry 4.0. it is well-suited analysis for identifying and analyzing complex, and context-specific phenomena, such as the factors that impact OEE in the manufacturing process. Thematic investigation is a multi-stage approach in this study that typically involves the following steps:

- Familiarization: becoming familiar with the interview data and reading through it to identify potential themes and patterns in the manufacturing process.
- Coding: data segments that are appropriate to the study issue (enhancing OEE through industry 4.0) are systematically created, marked, and given descriptive codes.
- Theme development: grouping the codes into comprehensive categories, like similar trends, patterns, or contacts created in the data.

- Reviewing and refining: reviewing the themes to make sure they appropriately reflect the data and making any required adjustments and filtering
- Reporting the findings: presenting the findings, typically by highlighting the themes and offering illustrations or relevant observations from the examination of the interview data.

This analysis gives a comprehensive understanding of the interview and enquires data and points out prospective areas where industry 4.0 for possible solution.

In general, on a big data analysis (BDA), the missing data is filled by a random forest (RF) of machine learning algorithms that are used to handle the missing data. Handling the missing data was done in two ways: the first was filling the missing data with the mean, media, and mode categories to recognize or interpret the pattern in big data by applying pattern recognized trained with data machine learning types used to predict OEE, and the second was dropping data points with missing values.

3.9.3 Integrated data analysis method

Enhancement of OEE through the utilization of industry 4.0 involves analyzing data from various sources, such as operation and production systems, sensor data, and machine logbooks, to identify areas for improvement and opportunities for optimization. This includes analyzing data on machine uptime, operation, production output, and quality metrics to identify bottlenecks and inadequacies in the operational process. The data analysis also involves using advanced analytics techniques, such as machine learning, human-machine interface (HMI), and predictive solution, to identify the trends in the data and make predictions about future performance or recommendations. Additionally, the data analysis involves evaluating the impact of industry 4.0 technologies, such as automation and connectivity, on operations and identifying areas where these technologies can be further utilized to improve OEE. using tools such as cluster chart, root cause analysis, pareto chart (the single influenced one expresses the other), cause-and-effect diagram, and pie chart. Software such as Minitab statistical, Google-sheets, or spreadsheets used to organize and analyze data collected from primary and secondary sources. All this data should be analyzed to identify opportunities for improvement, develop and apply best manufacturing practices, and measure the impact of those practices on OEE.

The analysis of overall equipment effectiveness (OEE) in manufacturing processes was improved by the application of Industry 4.0. In order to identify patterns and trends, data is gathered and analyzed from primary and secondary sources, including machines, HMIs, employers, sensors, and other connected devices. Additionally, machine learning algorithms and other technologies are used to make more precise predictions about machine performance and maintenance requirements. Companies locate recursion problems, instrument adjustments to increase productivity and effectiveness of equipment by studying the data produced by production processes.

Utilizing big data analytics to examine engineering procedures and machine performance data in order to find potential areas for improvement is one type of analysis. In order to do this, it is necessary to gather and analyze data from sensors and other connected devices to identify patterns and give possible solution for the problem. It may also be necessary to use machine learning algorithms and other technologies to predict machine performance and maintenance requirements with greater accuracy.

3.10 Ethic consideration

Since respect for the dignity of research participants should be prioritized and full consent should be obtained from the participants prior to the study, the researchers explain to the respondents the purpose of the study and assure them that the information given will be held confidential and that their names will remain anonymous. The consent of all the intended respondents is required from all current participants in the big data collection. Hence, it can be said that the study was conducted in an ethical manner.

Chapter four

4 Data analysis, presentation, and findings

4.1 Introduction

This chapter focuses on answering the second two research questions related to equipment effectiveness in the manufacturing industry. since the first question is answered in the second chapter, Section 2.1. But the second and third questions are answered in this chapter. The second question is investigating the current overall equipment effectiveness trend of auxiliary grand machines in Hilina's energy-enriched food manufacturing industry. To address this question, secondary and primary data sources were utilized, including department logbooks, technical apps, smart machines (like sensor, tip trace, and micro leakage counter and recorder), observations, interviews, and inquiry form with respondents, operators, employers, and technical managers. Equipment characteristics most frequently associated with big losses during operations were identified based on scholarly sources and past company data. In addition, big data from Hilina energy enriched food manufacturing industry was analyzed to gain further insights. Identified losses were utilized to identify the root causes of losses, recursion or significant issues, and possible solution of equipment effectiveness in the manufacturing industry. Different data sources, including both primary and secondary, were used to examine the root cause as well as the underlying trends.

The third research question is developing a possible solution for auxiliary grand machines to enhance overall equipment effectiveness through the use of Industry 4.0 in the Hilina energy-enriched food manufacturing industry. Results of possible solutions from big data presentation and analysis from both primary and secondary sources were used to rank the factors contributing to these against big losses in the Hilina manufacturing industry as compared to good-class standards, with the aim of minimizing them. Finally, enhancing the OEE was conducted to compare the new findings with the existing ones after considering the possible solution's positive impact on auxiliary grand machines in the Hilina energy-enriched food manufacturing industry.

According to the study, enhancing any one of the three components of OEE (availability, performance, and quality) has a considerable impact on OEE as a whole. However, there is still a research data gap in figuring out how to engage industry 4.0 technology to best address these characteristics. More investigation is specifically required to establish the most effective strategies to incorporate real-time monitoring, data analytics, automation, and predictive maintenance into manufacturing operations. This is also required to determine the best practices for data usage for upskilling and training employees. By filling these knowledge and data gaps, firms may better utilize industry 4.0 technologies to increase OEE and overall operation effectiveness.

As described in the background section, the Hilina energy-enriched food production company has four main section or zone: the first zone is peanuts, grains, and raw materials zone. Product output is the quantity required to produce Plumpy nuts and Plumpy sup. To achieve this, unit includes the basic machine operations of roasting, sorting, and manual screening. The second section stores and illuminates quality-assured raw materials, while the remaining eight are additives: peanuts, sugar, palm oil, soy, Nata5, milk, cheese, and vitamins. Then the production section continues, which includes pre-blending, mixing, grinding, filtering, and treatment sections. And the fourth section, the durable part, is done by filling and packing the PCs and packing them in cartons. The production data collected from all areas is required to evaluate the plant's OEE (Meca Vital, 2020). Due to this, the operational work flow of the Hilina manufacturing industry is shown below in Figure 4.1.

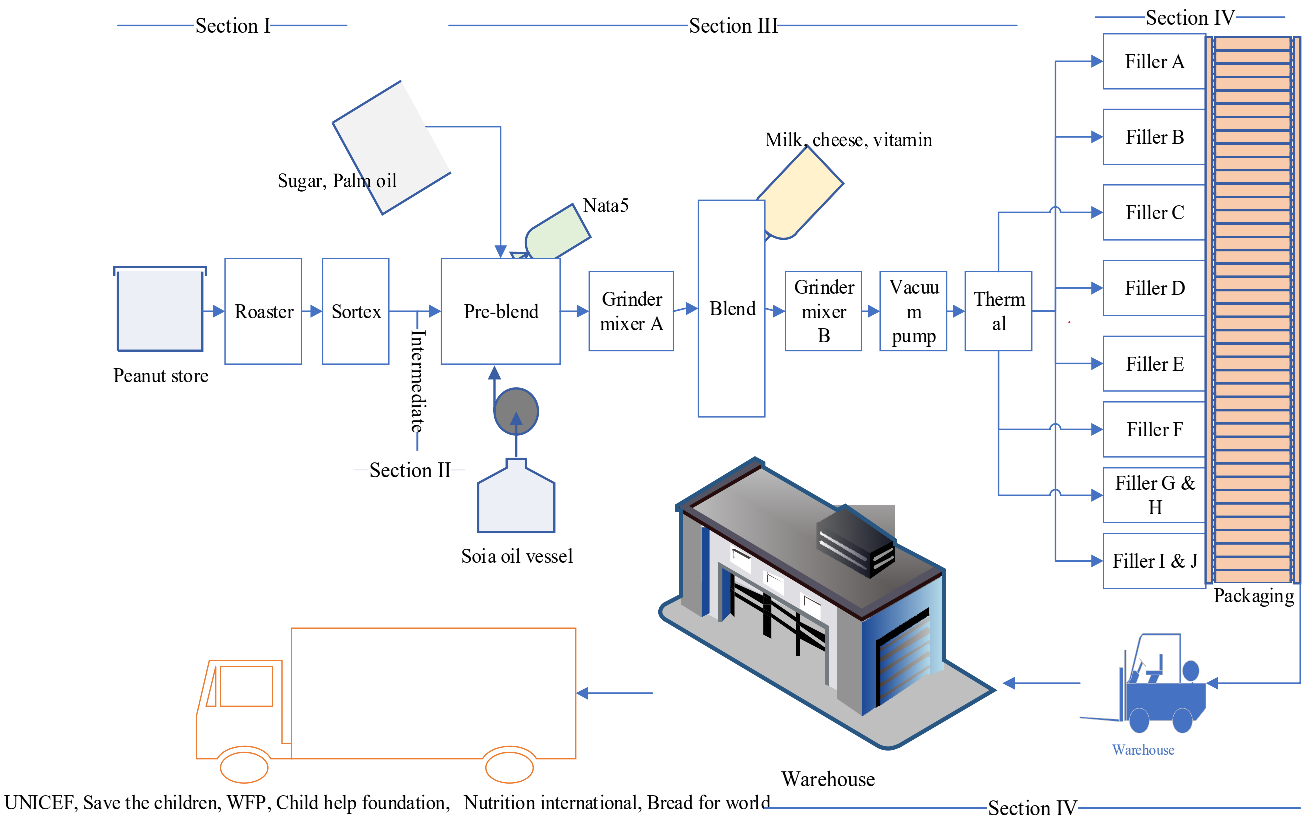


Figure 4.1 The overall representation of manufacturing process

4.2 Overall qualitative and quantitative data presentation

The Hilina-enriched food manufacturing industry recognizes and gives credit to all the sources of data related to the manufacturing information listed below. The collected data from the manufacturing process is utilised for analysis and evaluating the overall equipment effectiveness of the manufacturing process. Figure 4.1 is relied upon to determine the daily, weekly, and monthly equipment status, and production output, Additionally, Figure 4.1 contains data on the number of minutes lost and the frequency of breakdowns. The required information is gathered from each of the manufacturing sections in accordance with the manufacturing system shown above.

The information gathered spans the eight-month period from October 2022 to May 2023, but the data is covered from January 2022 to May 2023 To identify the current manufacturing system, process, recursion factors affecting OEE, and metrics of the manufacturing system, as well as to understand the system fluctuation on the variation bottleneck among the schemes and cutting-edge technology and tools (industry 4.0) on the improvement of OEE, a great deal of big data collected.

When it comes to OEE enhancement, the main things to consider are three metrics: availability (equipment running or not, i.e., planned and unplanned downtime due to breakdown or maintenance), performance (speed considering), and the last one, quality (scrap, defect, good, and total product on its process). After identifying the basic metrics, the next step is to present the data in a summary way.

The production data for 2022 is summarized below from the monthly output of each listed product found in Appendix IA from 1 up to 52 weeklies. The manufacturing in all sections according to Figure 4.1 classification is gathered. On Hilina enriched food factory the main ingredient is peanut for all production output peanut ratio is larger than other additives, so the below table 4.2 also we see the peanut losses on the auxiliary machines.

4.2.1 Overall quality data presentation focused on total production output and its losses

Table 4.1 Monthly production output and its losses

Month	Plan (in ton)	Total produce Plumpy Nut (in ton)	Total produce Plumpy Sup (in ton)	Sachet loss (in meter)	Total product produce (in ton)	Total defect (in ton)	Difference between produce to plan (in ton)
Jan	700	130.17	341.28	9081	471.45	0.98309	-228.55
Feb	700	476.03	10.2	16676.16	486.23	1.3722	-213.77

Mar	700	662.66	55.59	15927.9	718.25	1.49006	18.25
Apr	700	661.31	0	16235.86	661.31	1.57195	-38.69
May	700	257.47	192.76	11548.43	450.23	1.06589	-249.77
June	700	240.36	500.47	17841.57	740.83	1.45777	40.83
July	700	541.47	67.17	13605.31	608.64	0.99511	-91.36
Aug	700	616.83	0	17385.94	616.83	1.38526	-83.17
Sep	700	3.96	0	92.66	3.96	0.01838	-696.04
Oct	700	420.37	177	16768	597.37	1.30203	-102.63
Nov	700	239.89	454.83	26923.5	694.72	1.76289	-5.28
Dec	700	496.86	144.43	16669.6	641.29	1.27806	-58.71
Total in tone	8400	4747.38	1943.73	178755.9	6691.11	14.68279	-1708.89

Product package losses due to defect and machine problem

Month	each Plan (ton)	Additive on Nut (kg)	Additive on Sup (kg)	Sachet loss nut (meter)	Sachet loss sup (meter)	Product loss nut(ton)	Product loss sup(kg)
Jan	700	101	264	2685.47	6395.85	197.8	785.29
Feb	700	369	8	16422.16	254.04	1343.7	28.5
Mar	700	513	43	14189.85	1735.05	1299.98	190.08
Apr	700	512	0	16235.9	0	1571.95	0
May	700	199	149	6696.68	4851.75	678.26	387.63
June	700	186	386	5477.6	12363.7	495.1	962.67
July	700	419	52	11562.19	2043.15	815.59	179.52
Aug	700	478	0	17385.9	0	1385.26	0
Sep	700	3	0	92.66	0	18.38	0
Oct	700	326	137	11329	5439	824.91	477.12
Nov	700	186	352	8770.55	18152.9	580.47	1182.42
Dec	700	385	112	12459.9	4209.7	964.55	313.51
Total tone	8400	3677	1503	123307.86	55445.14	10175.95	4506.74

Product	1 Pcs	
Plumpy nut	100gram	15.07cm Sachet
Plumpy sup	92gram	14.90cm Sachet

Source: production, logbook, and data room

$$\text{Sachet loss for Plumpy nut (in cm)} = \text{weight of product in gram} * \frac{15.07\text{cm}}{100\text{gram}}$$

$$\text{Total product produce} = \text{Plumpy nut} + \text{Plumpy sup}$$

$$\text{Total defect} = \text{total product produce} - \text{Good product produce}$$

The aforementioned information was compiled from the weekly production report's total. The days on the left are workdays (364 * 23 hr. = 8372 hr.), and almost $15\frac{1}{2}\ days$ remains, for exception of Sunday and 14 holy days. When the actual output exceeds the intended values, some of the difference values from the data above are negative, and more demand is required. Additionally, it shows that the machinery is operating above their target output capacity; nevertheless, this does not mean that they are operating above their intended capacity. According to the above table, 79.66% of the actual output compared to the desired output, including the defective products, was produced, which is the ratio of 8400 tons to 6691 tons, or 0.7966 percent.

- **Yearly raw material loss on the process of Roaster plus Sortex machine**

Table 4.2 Raw material losses on auxiliary machine during the process

Summary January to December 2022 peanut loss on the process					
Type of peanut	Imported peanut		Local Peanut	Local + Imported peanut	
Unit	kg	Tone	kg	Kg	tone
Total Raw sorted peanut	2075000	2075	2777	2077777	2077.777
Infested peanut, size, color	92716	92.716	201	92917	92.917
Hull	73796	73.796	98	73894	73.894
Loss due to moisture	139804	139.804	218	140022	140.022
Roaster loss = Hull+ Moisture	213600	213.6	316	213916	213.916
Sortex loss= Infested, size, color	92716	92.716	201	92917	92.917
Total Loss = Roaster + Sortex	306316	306.316	697	415555	415.555
Loss %	14.76%	14.76%	25.10%	20.00%	20.00%
Remaining	1617976	1617.976	2263	1620239	1620.239

Source; production department (Appendix IB)

Percentage losses of local imported peanuts are covered at 25%, which is from 2,777 kg of peanuts; 697 kg of peanuts are defective, whereas imported peanut defects are covered at 14.76%, which is from 2,075,000 kg of peanuts; 306316 kg of peanuts are defective.

The machinery is operating above their target output capacity; nevertheless, this does not mean that they are operating above their intended raw material or peanut. According to the above table, 85.24% of the actual good-sorted peanuts were imported rather than local peanuts (74.90%), losses due to differences in the process. The overall good-sorted peanut ratio is 80 percent.

4.2.2 Overall availability data presentation focused on downtime

In the Hilina manufacturing industry, most downtime is recorded on filler and packaging machines rather than other auxiliary machines, since downtime is unavailable or not functioning at the time of operation due to technical or other factors when the requirements are fulfilled. To enhance the OEE of the company, significant focus was placed on Figure 4.1, Section IV. Downtime and its many types are given in the table below, which is a summary of Appendix IC. Downtime is the first category of profitability in the manufacturing industry.

Table 4.3 Filler and packaging downtime

Week	Total downtime (planed + unplanned downtime in min.) January to December 2022							
	A	B	C	D	E	F	G and H	I and J
1	6101	10080	6475	5475	5065	5075	11314	0
2	2733	9660	3970	5030	4251	5942	4960	0
3	5485	8601	4168	8217	6784	9940	8206	0
4	7831	9600	5565	9175	7664	9600	8336	0
5	8287	10080	8814	9339	9322	10080	14804	0
6	8845	5194	5219	7340	8700	8700	17400	1540
7	9235	4892	5122	9512	9755	9960	19920	8314
8	9414	4781	3731	8975	9595	9595	19190	14038
9	9540	6585	6330	9470	9540	9540	19080	16080
10	10560	6193	5701	9600	7878	9600	15986	8470
11	10080	3355	5720	4907	4665	10020	4560	2892
12	10080	2012	1495	4750	4795	10060	4032	4298
13	10020	2774	4469	5722	3377	8521	4362	4834
14	9660	2414	4041	5783	3193	5272	12224	12324

15	9240	4066	4078	5751	5500	7309	13992	15940
16	10020	3701	3089	4467	4961	5134	19086	19108
17	9660	5287	2067	2172	3666	2439	6126	11632
18	10020	9021	6065	5992	6605	8779	15310	18080
19	10080	2658	2555	4200	2538	4550	8890	10772
20	10080	3165	3105	1410	1363	2204	16958	17240
21	10440	5997	4240	3964	4943	4280	14556	13570
22	7200	2475	2071	1782	7159	2033	2946	2188
Total	194611	122591	98090	133033	131319	158633	262238	181320
Rank on downtime	7	2	1	4	3	5	8	6

Source: technique and production department, logbooks, SCADA, tip track

This table shows that which filler and packaging machine has the largest and least downtime. The data shows that they are operating below planned time, which results in increased time losses compared to their target output capacity; nevertheless, this does not mean that they are operating above their intended capacity. According to the above table, filler and packaging types C, B, I, J, G, and H are good relative to A, D, E, and F since the longest downtime is these least effective in equipment effectiveness. Due to this data, we can analysis and find out the most recursion problem on each filler and packaging machine.

4.2.3 Overall performance data presentation focused on total production output and its losses

Table 4.4 Filler and packaging speed performance

Mont	A	B	C	D	E	F	G and H	I and J	Total	Efficiency %	Design performance
Production speed PCS/min. =50Pcs/min											
Jan	2253	2617	2759	498	2829	2424	1332	1332	16044	35.94	44640
Feb	2257	2947	2812	0	2474	2485	2691	2691	18357	43.96	41760
Marc	2686	2871	2646	528	2786	2554	2679	2679	19429	43.52	44640
Apr	1724	3003	3004	889	3031	3081	2956	2956	20644	47.79	43200
May	1841	2792	2513	2055	3013	2760	3019	3019	21012	47.07	44640
June	2570	2552	2739	2376	2637	2446	2914	2914	21148	48.95	43200

Jul	1640	2428	2228	1476.	2081	2040	2673	2673	17239.	38.62	44640
Aug	2659	2440	2791	1541	2453	2102	3365	3365	20716	46.41	44640
Sep	2541	2476	2329	2076	2664	2749	2964	2964	20763	48.06	43200
Oct	2958	3147	3299	2786	3114	3208	2076	2076	22664	50.77	44640
Nov	1139	1314	2498	1671	1891	2519	1649	1649	14330	33.17	43200
Dec	0	618	2889	2662	2618	3095	2724	2724	17330	38.82	44640
Total	24268	29205	32507	18558	31591	31463	31042	31042	229676	43.58	527040
Perf%	46.45	55.89	62.21	35.52	60.46	60.22	59.41	59.41			
Rank	7	6	1	8	2	3	4	4			

Source: production department, SCADA for more in Appendix I D.

In 2022, there were 1045 shifts, and the shift per minute is 50 pieces per minute, so the standard for all is 1045 * 50 = 52,250 shifts per year. In accordance with performance as shown in the above table, data is operating below planned performance, which results in increased product losses compared to their target output capacity; nevertheless, this does not mean that they are operating above their intended. According to the above table, filler and packaging types C, E, and F have good performance relative to A, B, D, and F, since this is the least effective in equipment effectiveness. Machine performance of 62.21% (C) is relatively good for other fillers and packaging but still below company conformance of standard.

4.3 Overall qualitative and quantitative data analysis and findings

In industrial companies, overall equipment effectiveness serves as a measurement and improvement indicator tool. These are essential for demonstrating the level of effectiveness and the elements that have the greatest impact on the business. The OEE of each piece of equipment should be examined since it serves as a benchmark and a progressive approach for measuring and examining the machinery across the entire system using big data. Missing data is filled first by using pattern recognized trained with data, then by random forest (mean, mode, and media). (Haddad, 2021) claims that OEE, a well-known measuring technique, can accurately reflect the state of the equipment at the production site and is frequently used in the industrial sector to assess the equipment's efficacy for the improvement solution.

The equipment is categorized in order to analyze the OEE of the Hilina manufacturing industry, i.e., auxiliary, filler and packaging machines. However, based on the available literature, there is potential data on the root causes of downtime, many of which are difficult to measure and quantify. In Hilina-enriched food manufacturing industry, issues such as raw material and spare shortages, operator error or misalignment, or blancher adjustment, maintenance are not easily detectable via machine metrics and, consequently, are not fully accounted for in OEE calculations. Thus, more investigation is needed to identify and measure these less obvious sources of downtime and develop more effective strategies to mitigate them. Additionally, there is a need for more hard and standardized methods to measure and compare OEE data across different manufacturing processes in order to facilitate benchmarking and best practice sharing.

These are industry 4.0 technologies. That is, following manufacturing processes, data is often collected manually, automatically and analyzed retrospectively, which leads to delays in identifying issues that affect OEE, and this is the major reason for big losses. By contrast, industry 4.0 technologies such as advanced analytics, microtechnology, and tip trace machines allow for real-time data collection and analysis, which helps operators quickly identify and address issues that affect OEE. Large but unrecognized data gaps in manufacturing operations are primarily due to raw material, maintenance, breakdown, and spare parts shortages, employee burnout or absenteeism at the right work place, human error, and the so-called bad habits of workers: they have their bodies, but their minds are not there. The result is that the machines are engaged in unwanted work, resulting in a loss of quality and performance, then it is likely that the machines are not being utilized effectively and efficiently. In the Hilina-enriched food manufacturing industry, most big losses occur on auxiliary grand machine, as shown in tables 4.4, 4.5, and 4.6 below.

When it comes to analysis on figure 4.1, the part of auxiliary grand machine, or section I to IV, downtime on daily base that is 23hr per 364days=1440min per days is planned working time.

$$\text{Downtime percentage lose for each machine } = \frac{\text{Downtime for eachmachine}}{\text{Planned working time}} \ldots (equ\ 4.1)$$

$$\mathrm{DTi} = \frac{\mathrm{RDTi}}{\mathrm{PWTi}}$$

Were

DTi= recorded downtime of machine i

Planned working time of machine i per daily=23hr/364days=1380min/364days,

Planned working time machine i in a year 23hr*364=8372hr= 502320min.

-1hr for each day and 1days add in a year is for recover holyday, maintenance, and other issues.

So, the average daily downtime of grand auxiliary machine and auxiliary machine (filler and packaging machine)

Section I (Raw material preparing zone)

$$\text{DTroaster} = \frac{70 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.543$$

Sortex is including machine and manual handled filtering and shine peanut.

$$\text{DTsortex} = \frac{40 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.290$$

Section II and III (Production zone and sorting zone)

$$\text{DTpre} - \text{blend} = \frac{55 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.039$$

$$\text{DTgrinder \& mixer A} = \frac{65 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.0471$$

$$\text{DTblend} = \frac{65 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.0471$$

$$\text{DTgrinder \& mixer B} = \frac{55 min/day}{1380\text{min/day}} = 0.039$$

$$\text{DTvacum pump} = \frac{25 min/day}{\frac{1380\text{min}}{\text{day}}}$$

$$= 0.0181$$

$$\text{DTthermal treatment} = \frac{25 min/day}{\frac{13800\text{min}}{\text{day}}}$$

$$= 0.0181$$

Section IV (Finishing and processing zone)

$$\text{DTfiller \& packaging} = \frac{432 min/day}{\frac{13800\text{min}}{\text{day}}}$$

$$= 0.313$$

The summarized table below

Table 4.5 Downtime status to unknown and known reason in daily average status

Average data analysis of auxiliary grand machine daily status in 2022

Equipment losses	Reason of stoppage	Expectation working time (in min. Per-day)	Downtime (in min. Per- day)	Reason of stoppage	Downtime (in min. per-day)	DT in percent%
Roaster machine	Unknown	1380	45	CIP	30	5.43
Sortex machine	Unknown	1380	25	CIP	15	2.90
Pre-Blend machine	Unknown	1380	25	CIP	30	3.99
Grinder & Mixer A	Unknown	1380	40	CIP	25	4.71
Blend machine	Unknown	1380	35	CIP	30	4.71
Grinder & Mixer B	Unknown	1380	30	CIP	25	3.99
Vacuum pump	Unknown	1380	10	Check	15	1.81
Thermal treatment	Unknown	1380	10	Check	15	1.81
Filler & packaging	Unknown	1380	320	CIP	112	31.30

Source: technical manager, logbook, data room, team leader, SCADA (per-day in average)

Availability is the ratio of operating time to the planned production time and availability loss is the time where the organization is not undertaken the processing of manufacturing at the time of net operating period (Abd Rahman, 2020).

$$\text{Availability} = \frac{\text{Actual available time}}{\text{Planned availabile time}} = \quad \text{from (equ 2.1)}$$

$$= \frac{\text{Total working time}}{\text{Total panned working time}}$$

Table 4.6 Overall status of auxiliary grand machine

Overall status of auxiliary grand machine in 2022					
Equipment losses	Reason of downtime	Total panned working time (in hr.)	Downtime (in hr.)	Total working time (in hr.)	Availability (in %)
Roaster machine	Unknown	8372	921.48	6180.21	73.82%
Sortex machine	Unknown	8372	966.83	6263.93	74.82%
Pre-Blend machine	Unknown	8372	931.52	6160.12	73.58%
Grinder & Mixer A	Unknown	8372	1020.04	6041.24	72.16%
Blend machine	Unknown	8372	989.29	6044.58	72.20%
Grinder & Mixer B	Unknown	8372	1047.66	5985.98	71.50%
Vacuum pump	Unknown	8372	995.06	6265.60	74.84%
Thermal treatment	Unknown	8372	956.55	6342.63	75.76%
Filler & packaging	CIP	8372	174.42	7101.69	84.83%
Roaster machine	CIP	8372	87.21	7230.76	86.37%
Sortex machine	CIP	8372	174.42	7091.64	84.71%
Pre-Blend machine	CIP	8372	145.35	7061.27	84.34%
Grinder & Mixer A	CIP	8372	174.42	7033.88	84.02%
Blend machine	CIP	8372	145.35	7033.64	84.01%
Grinder & Mixer B	Checking	8372	58.14	7260.66	86.73%
Vacuum pump	Checking	8372	58.14	7299.17	87.19%
Thermal treatment	CIP	83720	651.16	54614.84	65.24%
Filler & packaging	CIP	8372	174.42	7101.69	84.83%

Source: technical manager, logbook, data room, team leader, and, SCADA

The total downtime for unknown and known reasons, the production line can add up the downtime for series operational machines only, not for parallel operation.

When we added the total down time in the case of each machine as individual as series operation the time is to be 603mintus (10hr) downtime, in this analysis the remaining time which is

$$1440 - 603 = 837\text{min} \approx 13.95\text{hr} \text{ are Ineffective time per day in average}$$

In another view operation is never continued by pedal, while in parallel we can proceed. Therefore, in this case, the total downtime would be 12 hours per day. This means the equipment is only operating at 50% efficiency (i.e., 24 hours per day minus 12 hours of downtime = 12 hours of actual operation. For this production line's efficiency, it is helpful to identify the root causes of the equipment failures and address them systematically.

In one day, each machine has a 1440-minute working capacity, but due to known and unknown reasons, the average working time is half of the capacity, which means that the average capacity efficiency of the grand machine covers 50% of the conformance design as shown in the data.

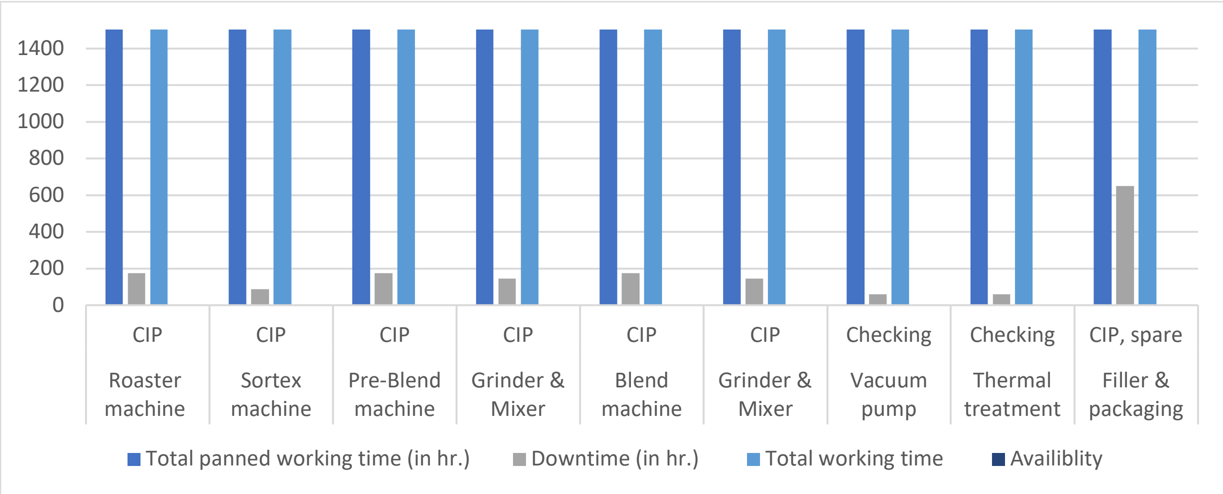


Figure 4.2 Basic machine average downtime for known reasons in 2022

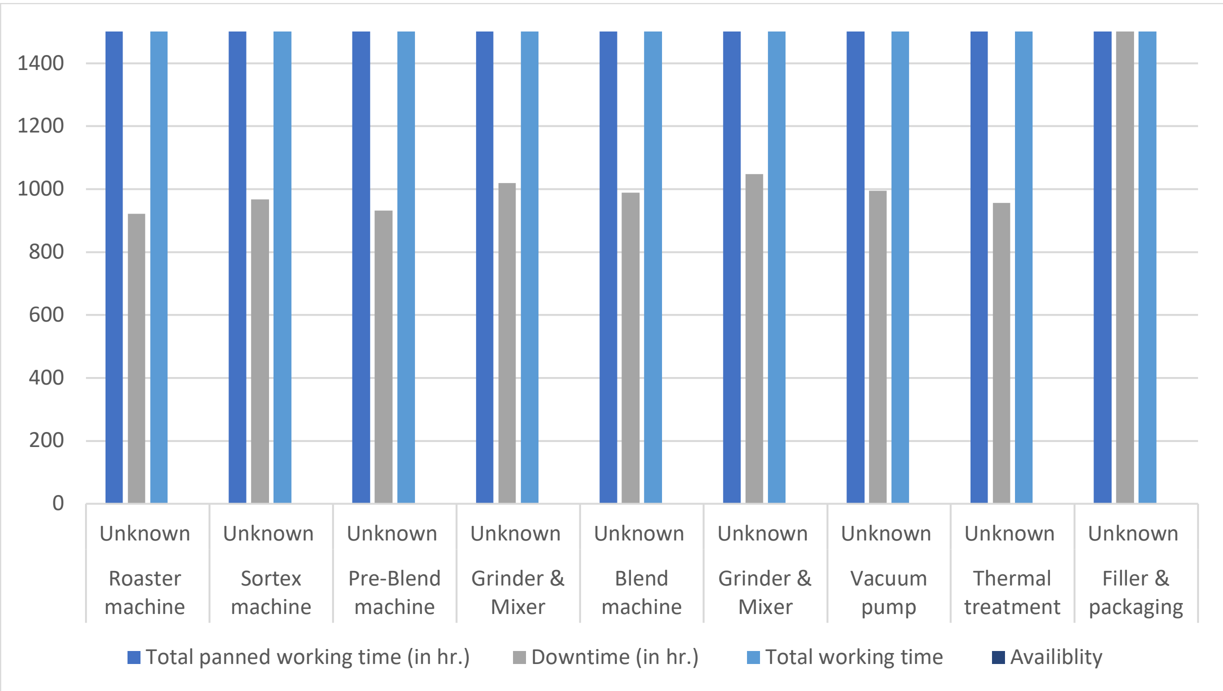


Figure 4.3 Basic machine average downtime for unknown reason in 2022

4.3.1 Analysis trends and findings of organization OEE

By acquiring and reviewing data on the factors that drive the losses, such as manufacturing performance, scrap rates, and downtime, a manufacturing company can monitor the crucial OEE metrics over time, such as availability, performance, and quality losses caused by OEE losses.

- One method is to use OEE metrics, which automates data collecting, processing, and provides real-time insights into equipment performance and losses. Finding patterns and trends in the data is essential for making well-informed decisions about how to reduce losses and increase OEE.
- Using databases or Google Sheets to manually track OEE metrics and display the data using graphs and charts is another approach. As a result, it is simpler to identify trends in the data and evaluate the consequences of changes.

By recording OEE measures and analyzing patterns over time, the companies identify areas for improvement and make data-driven decisions to maximize equipment performance and reduce losses. Combining data analysis tools and process optimization approaches will help a manufacturing organization identify the underlying reasons for OEE losses and monitor trends.
The first approach is to use the OEE in most major losses area (filler & packaging machine), which offers real-time insights on equipment performance and losses while automating data collection and processing technology like tip track equipment's. By identifying patterns and trends in the data, you can make intelligent decisions about how to reduce losses and increase OEE. Determine the main reasons for downtime equipment using Pareto charts, and then apply root cause analysis approaches to identify root causes those problems. While the second approach involves identifying and removing waste throughout the manufacturing process using the concepts of lean manufacturing, by decreasing downtime, lowering scrap rates, and increasing manufacturing capacity, this helps to enhance OEE. To find areas for improvement and make changes, process flow analysis.

All-purpose manufacturing industries identify areas for improvement and make data-driven decisions to maximize equipment performance and lower losses by tracking OEE measurements and examining trends over time. In order to increase overall equipment effectiveness, it is possible to pinpoint the primary causes of OEE losses by fusing data analysis tools with process improvement methodologies.

On the other hand, in addition to mathematical analysis, root cause analysis is essential to investigate the current investigation of overall equipment effectiveness in the manufacturing industry. Root cause analysis (RCA) is a well-liked and frequently applied technique that aids in determining the initial cause of the issue or loss. It seeks to locate the core of a problem by using a certain set of procedures and related tools, allowing for the determination of what occurred, why it occurred, and what can be done to lessen the risk that it will occur again. According to RCA, events and systems are interrelated. Utilizing this technology was therefore deemed crucial in order to identify the underlying causes of the downtimes, speed loss, and quality loss that the industry producing Hilina-enriched foods is currently experiencing.

Since looking deeper to figure out what's causing a problem can fix the underlying systems and processes so that it goes away for good, RCA, following its basic steps, was used to identify the root causes underlying the common downtime, speed, and quality losses in the study as presented in this section. Hence, using the basic steps of RCA, the root causes of the common downtimes, speed loss, and quality loss are analyzed in Sections 4.3.2, 4.3.3, and 4.3.4 below.

Step one: problem definition

There are longer downtimes, speed and quality losses encountered on the majority of production days in the Hilina-enriched food manufacturing industry.

Step two: data collection and analysis

The common reasons for the occurrences of the observed downtimes, speed, and quality losses (through the logbook, technical app, sensor, direct observation, and formal and informal interviews) were also recorded and arranged based on their frequencies. From those findings, it was seen that almost all the reasons for common downtimes, speed and quality loss occur repeatedly on a daily basis in the operation of the company at a differing rate. Hence, it was found necessary to analyze which causes highly affect the smooth flow of the operation by occurring for longer durations and scrap, as the company needs to identify and focus on severe problems and prioritize addressing them through corrective actions. To do so, a pareto chart was used after arranging these reasons for downtimes, speed and quality losses according to their severity rate depending on the duration they lasted (using Minitab, a spreadsheet or Google Sheets).

The data presented below was mainly analyzed using the 80-20 (Pareto) rule along with the Always Better Control (ABC) analysis, which states that in many events, 80% of the effects come from 20% of the causes (Naoum V etal, 2016). That is, twenty percent of the activities are responsible for eighty percent of the outcomes or results. To perform this analysis, a list of downtime causes is generated in top-down order based on their duration. Category A includes the top 20 percent of the listed causes, which account for 80 percent of the duration recorded on the entire list. Category B is made up of the next thirty percent of causes, which represent approximately fifteen percent of the total duration recorded. Category C comprises the bottom fifty percent of the causes, which account for just five percent of the total downtime, speed and quality losses recorded. This categorization was used as it provides a clear basis for determining how stringent the controls should be for managing these three categories of events that result in downtime. Category A, especially the ones that can be improved, should have the tightest controls. Category B items require less careful oversight, and Category C items should involve the least administrative resources possible for management.

According to the table and figure of the record and analysis of downtime, speed, and quality losses caused when producing Plumpy Nut and Sup, it can be seen that challenges that occurred in auxiliary machines and filler and packaging machines, for instance CIP delay, filler labeler stoppage, late production start-up, and raw material neatness, fall under the "A" class. This in turn implies that these causes are responsible for the majority of the downtime, speed, and quality loss encountered during Plumpy Nut and Sup's production process and that efforts to reduce them as much as possible should be prioritized.

Step three: identification of possible causal factors using cause-and-effect diagrams

Step four: root cause identification

From the output of the cause-and-effect diagram on figure, it was identified that equipment losses were due to a shortage of maintenance tools, trainings, lack of skill, , the latest technology, a lack of easy problem identification skills, a raw neatness, a delay in responding to quick response requiring events by operators (e.g., picking up fallen PCs from the conveyor before blocking the path), the unavailability of machine accessories, a lack of emphasis and awareness on the importance of the supervisor's closer follow-up, time wastage during trial-and-error adjustment processes, an imbalance of the shield tank capacity, and recursion problem on auxiliary and filler and packaging machine are listed on.

Finalizing the process of identifying the origin and primary causes of longer downtimes, speed and quality loss using a specific set of steps along with associated tools and reducing the above list of root causes into fewer specific categories makes the process of managing and applying suitable control actions easier and possible solution. Therefore, the identified root causes were grouped and represented by broader independent variables such as industry 4.0 technology and tools, that is best manufacturing practice, and, big data presentation, machine accessories, following the fact that the causes of the company's problem fall under one or more of these categories. Consequently, these variables are further studied through the data from review responses.

4.3.2 Availability losses trend analysis and findings

A manufacturing organization like Hilina food PLC has availability losses due to a variety of causes, such as equipment failures, maintenance tasks, operator error, and supply chain disruptions. Utilize both quality improvement procedures and data analysis tools to determine the underlying source of these problems.

Identifying trends over time is accomplished by analyzing data on important performance indicators like mean time between failures (MTBF), mean time to repair, and overall equipment effectiveness (OEE), of which areas are common repetitive failures. This is the first criteria to calculate the real issues. Which is

$$\text{MTBF} = \frac{\text{Total operational time}}{\text{Total number of failures}} \ldots\ldots\ldots\ldots.(\text{equ } 4.2)$$

$$\text{MTTR} = \frac{\text{Total maintenace time}}{\text{Number of repair}} \ldots\ldots\ldots\ldots\ldots.(\text{equ } 4.3)$$

Good machine status standard value is MTBF is more than 130hrs, while MTTR is below 5hr (Nurprihatin, 2019). Determine the root causes of availability losses and employ root cause analysis methodologies like the fishbone diagrams.

Once the primary factors causing availability losses have been determined, specific solutions to these problems could then be developed and put into practice using data-driven decision-making, and predictive maintenance. These remedies include improvements to the equipment itself, adjustments to the processes involved, preventative maintenance procedures, or other interventions designed to save downtime, improve equipment effectiveness, and increase overall availability.

$$\text{Availability of mache i} = \frac{\text{Actual available time mache i}}{\text{Planned availabile time mache i}} = \quad \text{from (equ 2.1)}$$

$$= \frac{\text{Total working time mache i}}{\text{Total panned working time mache i}}$$

Table 4.7 Availability of auxiliary grand machines

The overall operation of auxiliary grand machine status from January to December 2022

Equipment	Number of failures	Total working time ((in hr.)	Total downtime (in hr.)	Total panned working time (in hr.)	Loss in %
Roaster machine	3(1st,2nd,3rd chamber)	7276.11	1095.89	8372	13.09%
Sortex machine	2(camera, pneumatic)	7317.97	1054.03	8372	12.59%
Pre-Blend machine	2 (level sensor, pump)	7266.06	1105.94	8372	13.21%
Grinder & Mixer A	2 (file, brushes)	7206.62	1165.38	8372	13.92%
Blend machine	2(level sensor, pump)	7208.29	1163.71	8372	13.90%
Grinder & Mixer B	2 (agitator, file)	7178.99	1193.01	8372	14.25%
Vacuum pump	2 (mechanical seal, gasket)	7318.80	1053.20	8372	12.58%
Thermal treatment	2 (thermal sensor, pneumatic line)	7357.31	1014.69	8372	12.12%
	Total	58130.15	8845.85	66976	86.79%
Filler & packaging	13 (printer, eye mark, knife, alignment, three-way valve, horizontal leakage & seal, vertical leakage & seal, dose, clutch, sealing temperature, alignment,)	55266.00	28454.00	83720	33.99%

Source: technical manager, logbook, and team leader, SCADA (Appendix I C & I E)

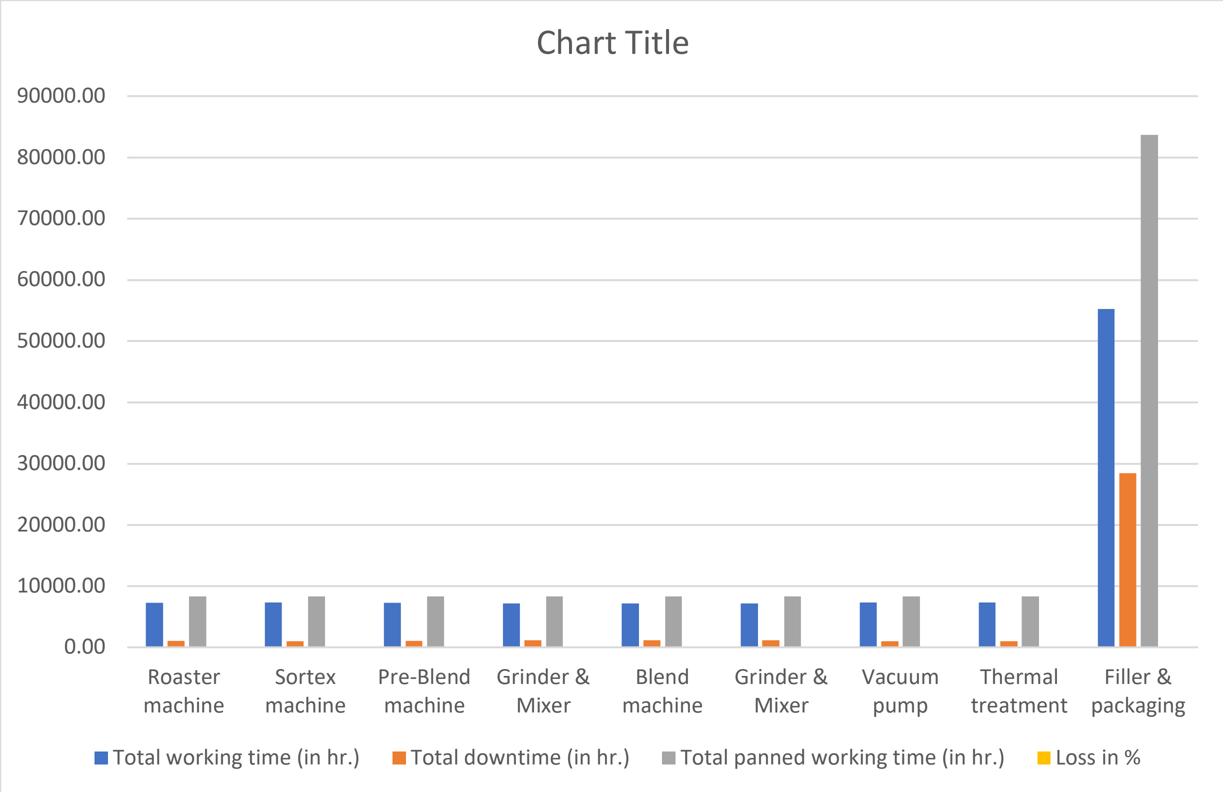


Figure 4.4 All-over auxiliary grand machine status

The availability of the above table is fulfilled by the following mathematical calculation

$$\text{Availability auxilary machine } = \frac{\text{actual available time auxilary machine i}}{\text{planned available time auxilary machine i}} (from\ equ\ 2.1)$$

$$= \frac{\text{Total working time of auxilary machine i}}{\text{Total Planned working time auxilary machine i}}$$

Were:

Machine i= roaster, Sortex, pre-blend, blend, grinder and mixer A & B, vacuum pump, thermal treatment, filler and packaging machine

Section I (Filtering raw material zone)

$$\text{Availabilty of roaster machine } = \frac{\text{Total working time of roaster}}{\text{Total Planned working time roaster machine}}$$

$$= \frac{7276.11\text{hr}}{8372\text{hr}}$$

$$= 0.8691 = 86.91\%$$

$$\text{Availabilty of Sortex machine } = \frac{\text{Total working time of Sortex machine}}{\text{Total Planned working time Sortex machine}}$$

$$= \frac{7317.97\text{hr}}{8372\text{hr}}$$

$$= 0.8741 = 87.41\%$$

Section II & III (Sorting and Production zone)

$$\text{Availabilty of pre} - \text{blend machine } = \frac{\text{Total working time of pre} - \text{blend}}{\text{Total Planned working time pre} - \text{blend machine}}$$

$$= \frac{7266.06\text{hr}}{8372\text{hr}}$$

$$= 0.8641 = 86.41\%\%$$

$$\text{Availabilty of grinder\&mixer machine A } = \frac{\text{Total working time of grinder\&mixer}}{\text{Total Planned working time grinder\&mixer}}$$

$$= \frac{7206.62\text{hr}}{8372\text{hr}}$$

$$= 0.8608 = 86.608\%$$

$$\text{Availabilty of blend machine } = \frac{\text{Total working time of blend machine}}{\text{Total Planned working time blend machine}}$$

$$= \frac{7208.29\text{hr}}{8372\text{hr}}$$

$$= 0.8610 = 86.10\%$$

$$\text{Availabilty of grinder\&mixer machine B } = \frac{\text{Total working time of grinder\&mixer B}}{\text{Total Planned working time grinder\&mixer B}}$$

$$= \frac{7178.99\text{hr}}{8372\text{hr}}$$

$$= 0.8575 = 85.75\%$$

$$\text{Availabilty of vacuum pump machine } = \frac{\text{Total working time of roaster}}{\text{Total Planned working time roaster machine}}$$

$$= \frac{7318.80hr}{8372hr}$$

$$= 0.8788 = 87.88\%$$

$$\text{Availabilty of thermal treatment machine } = \frac{\text{Total working time of roaster}}{\text{Total Planned working time roaster machine}}$$

$$= \frac{7318.80hr}{8372hr}$$

$$= 0.8788 = 87.88\%$$

Section IV (Finishing and processing zone)

$$\text{Availabilty of filler \& packaging machine} = \frac{\text{Total working time of roaster}}{\text{Total Planned working time roaster machine}}$$

$$= \frac{55266min}{284452min} =$$

$$0.6601 = 66.01\%$$

The above figure 4.4 shows each grand auxiliary machine's status on downtime, planned and actual working time, and its availability. Based on the above data analysis, the overall availability of auxiliary grand machines from January to December 2022 ranged from 54.95% for the filler and packaging machine to 87.88% for the thermal treatment machine. The total availability across all machines was 86.79%. The filler and packaging machines had the lowest availability at 54.95% due to issues with the printer, eye mark, three-way valve, knife, alignment, dose, and clutch. This suggests the filler and packaging machines were the largest sources of downtime and failures. Other machines with relatively lower availability include the Grinder & Mixer A at 86.08% and the Pre-Blend machine at 86.79% due to issues like brushes, satire, level sensors, and pumps.

Focusing efforts on resolving issues with the filler and packaging machine components as well as regular maintenance and component replacement for machines like the grinder, mixer A, and pre-blend machine could help increase the overall availability of the auxiliary grand machines. However, given the limited details provided, a thorough review of the failure logs, technical reports, and equipment condition would be needed to identify and implement targeted reliability improvement measures.

To know the major influencer for availability losses and case issues in the factory-prepared Perot table, it depends on the ratio of working time to planned working time of each machine. This is the main influence factor of the machine and its trend availability as root causes for losses.

Table 4.8 Perot table of auxiliary and grand machine

Auxiliary grand machine	Total downtime (in hr.)	Cumulative	Percentage	Cumulative Percentage
Filler & packaging	27802.84	27802.84	77.95%	78.03%
Grinder & Mixer B	1047.66	28850.51	2.94%	80.97%
Grinder & Mixer A	1020.04	29870.54	2.86%	83.83%

Vacuum pump	995.06	30865.60	2.79%	86.63%
Blend machine	989.29	31854.89	2.77%	89.40%
Sortex machine	966.83	32821.72	2.71%	92.11%
Thermal treatment	956.55	33778.27	2.68%	94.80%
Sortex machine	966.83	34745.09	2.71%	97.51%
Roaster machine	921.48	35666.57	2.58%	100.10%

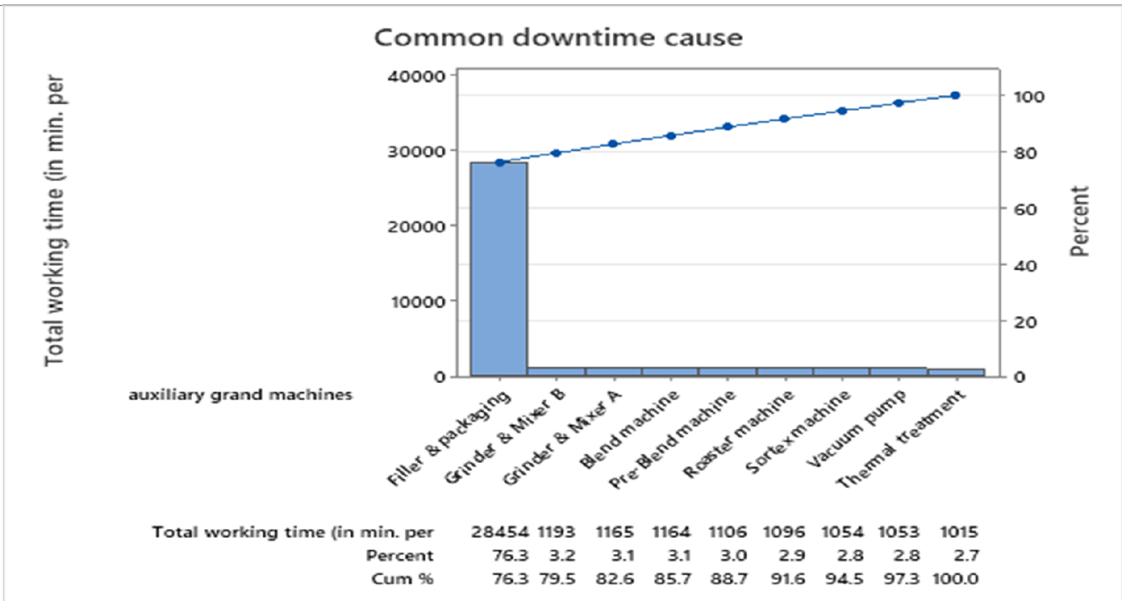


Figure 4.5 Perot analysis of auxiliary grand machines

The above Perot analysis clearly shows that the high downtime and lower availability of the filler and packaging machine seem to stem from issues with different components recursion problems, including the printer, eye mark, knife, alignment system, three-way valve, seals, and dose mechanism. Focusing replacement, maintenance, and repair efforts on resolving issues with these components could help improve the performance and uptime of the filler and packaging machine. The Pareto chart shows that the filler and packaging equipment has the highest percentage of total downtime at 77.95%, followed by grinder and mixer B at 2.94%, and grinder and mixer A at 2.86%. The remaining equipment has less than 3% of total downtime each.

The pie chart shows the percentage distribution of total downtime for each equipment. The largest portion belongs to filler and packaging at 78.03%, followed by grinder and mixer B at 2.97%, and grinder and mixer A at 2.86%. The rest of the equipment portions are less than 3% each.

These charts help to identify the most critical equipment that needs attention to improve the overall production performance and reduce downtime in the Hilina enriched food manufacturing context.

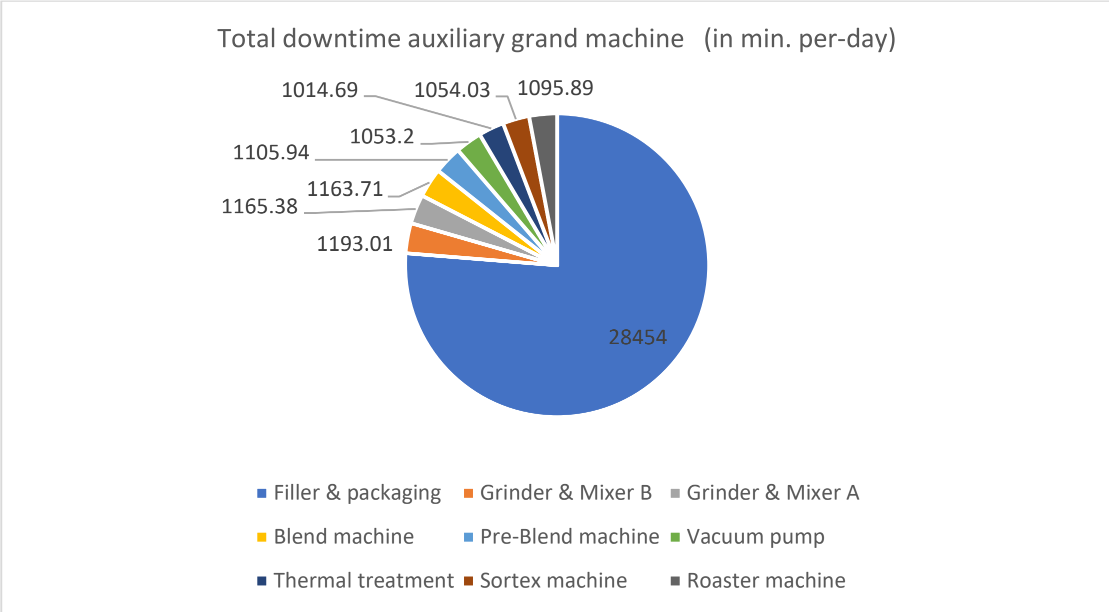


Figure 4.6 A pie chart representation of auxiliary grand machine downtime

Based on the above analysis, MTBF, MTTR, and the above table on the overall operation of auxiliary machines, it shows that there are more and more long-lasting delays and failures in filling and packaging machines in the Hilina Energy food processing industry. In addition to downtime, the above table also includes most of the reasons for downtime and equipment failure. Therefore, the Industry 4.0 level requires a special view of these machines and shows us to pay attention.

Were:

From table 4.7 the total number of failures = number of repetitions of failure in the company data room =Total number of failures = number of repetitions of failure in the company data room =58. Each failure and repair source are table 4.7.

$$\text{MTBF} = \frac{\text{Total operational time}}{\text{Total number of failures}} \ldots \ldots .. (from\ 4.2)$$

$$= \frac{\text{Total working time}}{\text{Total number of failures}} =$$

Average mean time between to failure in 365 days is equal to 4.90

$$\text{MTBR} = \frac{\text{Total maintenace time}}{\text{Number of repair}} \ldots \ldots \ldots .. (from\ 4.3)$$

$$= \frac{\text{Total downtime}}{\text{Number of repair}}$$

Based on the data provided for the overall operation of auxiliary grand machine status from January to December 2022:

To calculate MTBF for all over the auxiliary grand machine in general is

$$\text{Mean Time Between Failures} = \frac{\text{Total working time}}{\text{Number of failures}}$$

$$= \frac{58{,}130.15 \text{ hours}}{58 \text{ failures}}$$

$$= 1003.38 \text{ hours}$$

This indicates that between failures in auxiliary machines, the count is 1003.38 hours, which is equal to 41.8075 days in a year.

To calculate MTTR for all over the auxiliary grand machine in general is

$$\text{Mean Time To Repair} = \frac{\text{Total downtime}}{\text{Number of failures}}$$

$$= \frac{8{,}845.85 \text{ hours}}{58 \text{ repaire}}$$

$$= 152.79 \text{ hours}$$

The time to give solution also for auxiliary machines in general is 152.79 hours, which is equal to 6.37 days was count.

Therefore, in accordance with the status of the auxiliary machine, the relatively lower MTBF and higher MTTR indicate that the machines have more frequent failures and higher downtimes, likely due to issues with components and processes as mentioned in the reasons provided for each machine. Preventive maintenance to replace worn parts as well as process optimizations could help reduce failure rates and repair times to improve MTBF and lower MTTR.

Each auxiliary machine calculation of MTBF and MTTR is

MTBF for each machine:

Roaster machine:

$$\text{MTBF} = \frac{(7276.11 - 1095.89)}{3}$$

$$= 2060.74 \text{ hours} = 85.86 days$$

Sortex machine:

$$\text{MTBF} = \frac{(7317.97 - 1054.03)}{2}$$

$$= 3131.97 \text{ hours} = 130.49 days$$

Pre-Blend machine:

$$\text{MTBF} = \frac{(7266.06 - 1105.94)}{2}$$

$$= 3080.56 \text{ hours} = 128.36 \text{days}$$

Grinder & Mixer A:

$$\text{MTBF} = \frac{(7206.62 - 1165.38)}{2}$$

$$= 3020.62 \text{ hours} = 125.86 days$$

Blend machine:

$$\text{MTBF} = \frac{(7208.29 - 1163.71)}{2}$$

$$= 3022.29 \text{ hours} = 125.93 days$$

Grinder & Mixer B:

$$\text{MTBF} = \frac{(7178.99 - 1193.01)}{2}$$

$$= 2992.49 \text{ hours} = 124.69 \text{days}$$

Vacuum pump:

$$\text{MTBF} = \frac{(7318.80 - 1053.20)}{2}$$

$$= 3132.30 \text{ hours} = 130.51 days$$

Thermal treatment:

$$\text{MTBF} = \frac{(7357.31 - 1014.69)}{2}$$

$$= 3171.31 \text{ hours} = 132.14 days$$

Filler and packaging machines have 13 failures, as you mention in Table 4.7. This failure is repetitive in nature, and due to this, the maximum registered failure is 58. The number of failures and repairs in a year is also 58.

$$\text{MTBF} = \frac{(55266 - 28454)}{58}$$

$$= 462.27 \text{hours} = 19.26 days$$

This is for all filler machines; for each machine, divide the above by 10, since the plant has 10 filler and packaging machines. So, its equals to 46.227hr=1.92days failure is happened in filler and packaging machine.

MTTR (mean time to repair) is a measure of the average time required to repair a machine after a failure. It refers to the average time it takes to repair equipment after failure, not specifically an auxiliary machine.

MTTR measures how long an auxiliary machine is offline during repair; it does not directly indicate the skill level of engineers. While skilled engineers can help reduce MTTR through optimized repairs and preventive maintenance, other factors like parts availability, troubleshooting time, and repair complexity also impact MTTR. But this study considers the skilled nature of labour in its given solution. The phrase "this" indicates that the skill is not accurate. MTTR is one metric; it does not by itself indicate the skill level of engineers.

MTTR for each machine:

Roaster machine:

$$\text{MTTR} = \frac{1095.89}{3}$$

$$= 365.30 \text{ hours} = 15.22\text{days}$$

Sortex machine:

$$\text{MTTR} = \frac{1054.03}{2}$$

$$= 527.02 \text{ hours} = 24.96\text{days}$$

Pre-Blend machine:

$$\text{MTTR} = \frac{1105.94}{2}$$

$$= 552.97 \text{ hours} = 23.04\text{days}$$

Grinder & Mixer A:

$$\text{MTTR} = \frac{1165.38}{2}$$

$$= 582.69 \text{ hours} = 24.28\text{days}$$

Blend machine:

$$\text{MTTR} = \frac{1163.71}{2}$$

$$= \ 581.86 \text{ hours} = 24.24\text{days}$$

Grinder & Mixer B:

$$\text{MTTR} \ = \frac{1193.01}{2}$$

$$= \ 596.51 \text{ hours} = 24.85\text{days}$$

Vacuum pump:

$$\text{MTTR} \ = \ 1053.20\frac{1053.20}{2}$$

$$= \ 526.60 \text{ hours} = 21.94\text{days}$$

Thermal treatment:

$$\text{MTTR} \ = \frac{1014.69}{2}$$

$$= \ 507.35 \text{ hours} = 21\text{days}$$

Filer and packaging machine:

$$\text{MTTR} \ = \frac{28454}{58}$$

$$= \ 490.59\text{hours} = 20.44\text{days}$$

The reason for calculating MTBF and MTTR is to assess the reliability of each machine. Machines with higher MTBF and lower MTTR are more reliable and require less maintenance. The calculation also helps in identifying the root cause of failures and taking corrective actions to improve machine performance.

The number of filling and packaging machines at Hilina Food Enrichment Manufacturing Company is ten; of those ten, six are single-type machines, namely A, B, C, D, E, and F, and two are double-type machines, namely G and H, I, and J. One of the things that the organization should focus on is improving the overall equipment effectiveness of machinery, and the most important thing is to investigate the causes of the problem individually. Therefore, as outlined below, the reliability of these machines will help us reduce downtime and improve overall effectiveness in the selected latest season, i.e., from January to December 2022 (Week 1 to 52 = 365 days = 8760 hr = 525,600 min), but the conformance of the machine in the day is 23 hours, so 364 days = 8372 hours = 502320 are expected on each machine.

4.3.2.1 Cause and effect diagram auxiliary grand machine availability losses

The cause-and-effect diagram or fishbone diagram of auxiliary grand machine availability losses highlights the main factors that could influence the availability and downtime of the auxiliary grand machines: equipment failures, maintenance & operating methods, people and materials.

The number of failures and downtimes for each machine suggest issues with the machinery branch, specifically equipment failures for components like pumps, sensors, agitators and seals in machines like the Filler & packaging, Grinder & Mixer A and Pre-Blend machines. The methods branch could also contain potential issues like improper setups, maintenance procedures and control parameters that contribute to the equipment failures. A thorough investigation of failure logs, operation records and inputs from operator would be needed to identify the specific root causes and develop targeted improvement actions.

Looking at the data, it is clear that the filler and packaging equipment had the greatest number of failures and the highest total downtime (28454 minutes per day). This suggests that the root cause of failure and downtime for this equipment could be related to any of the six categories mentioned above. It is important to conduct further investigation to identify the specific causes and take corrective actions to address them. In contrast, the roaster machine had the lowest downtime (1095.89 minutes per day) and the highest availability (86.91%). This suggests that the root cause of failure and downtime for this equipment could be related to specific issues that need to be addressed to improve the performance of other equipment.

From the investigation the main causes of equipment failure and downtime can be categorized into six major categories: personnel, methods, machines, materials, measurement, and environment.

Overall, analyzing the causes of equipment failure and downtime using a fish-bone diagram can help identify the root causes and take corrective actions to improve the performance and reliability of the auxiliary grand machine in Hilina PLC.

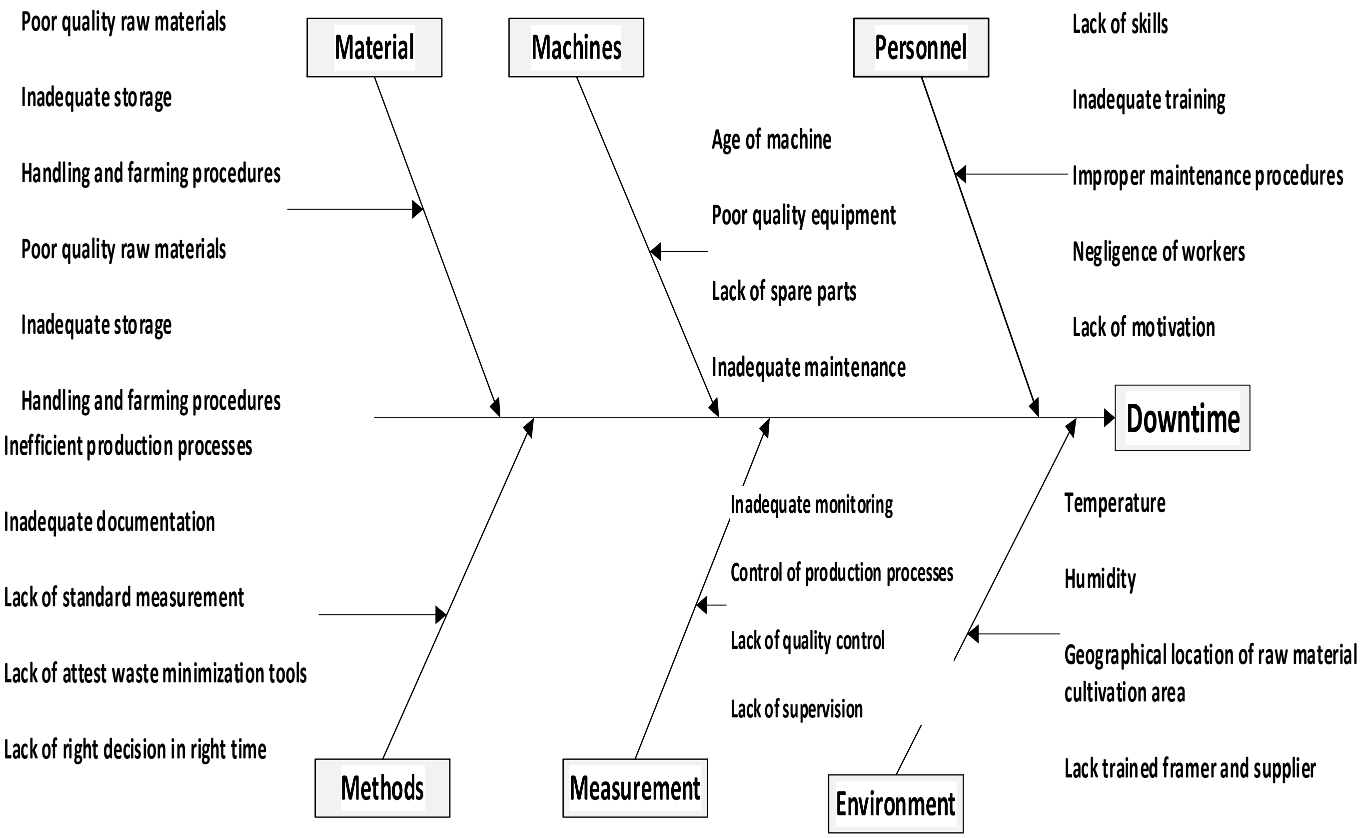


Figure 4.7 Fish bone diagram of auxiliary grand machine availability

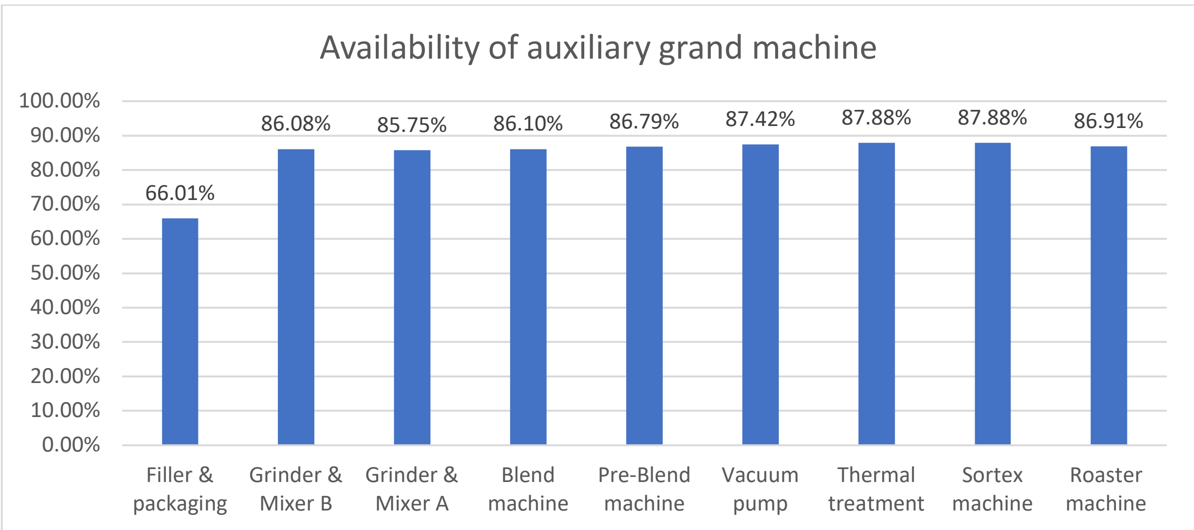


Figure 4.8 Availability of an auxiliary grand machine

The largest portion belongs to filler and packaging at 78.03%, followed by grinder and mixer B at 2.97% and grinder and mixer A at 2.86%. The rest of the equipment portions are less than 3%

each. So, from the mathematical calculation, the Pareto and pie chart of the auxiliary grand machine in the above description clearly suggested sectional detail investigation on filler and packaging machines, since this is the major influence for high downtime and small availability of machines in the factory. According to the description provided, it seems the filler and packaging machines contribute to the majority of downtime and low availability of machines. The number suggests investigating these machines further using big data analysis and focusing on the human-machine interface, as that could be a major factor influencing their high downtime.

The basic investigation, analysing relevant data sets from multiple parts of the filler and packaging machines' operation:

- Failure logs: identify components that fail most often and their root causes. Look for common patterns that point to design flaws or operational issues.
- Operator logs: analyse operator inputs, actions during failures and troubleshooting procedures to identify areas for optimizing human-machine interaction.
- Sensor data (like tip-track): monitor data from sensors in real time to detect anomalies early and predict potential failures.
- Image data (like machine vision): Analyse images from components like cameras, vision systems to detect defects and errors.
- Control data (random forest, pattern recognized trained with data): review control parameters, setpoints and programs to find unstable or improperly tuned values.

Using big data analytics techniques on the combined data sets can provide insights into design improvements, procedural changes, operator training needs etc. that can reduce downtime and improve availability of the filler and packaging machines. This in turn positively impact the overall availability of the auxiliary grand machine.

From this investigation, big data selected the following essential and directly related relevance data:

Table 4.9 Availability of filling & packaging machine on each filler

Time in hour for each 10 filler and packaging machine (A, B, C, D, E, F, G, H, I, J) in 2022

Machine	Rank according to small downtime	Loss %	N0 of failure	Total working time in hrs.	Total planned working time (in hrs.)	Total down time (in hrs.)	N0 of repair	Reason for this difference
A	10	58.92	They have differed failure in machine that is separatable and non- separatable in nature	3,439.22	8,372.0	4,932.78	They have differed failure in machine that is separatable and non- separatable in nature	Vertical & horizontal leakage & seal, eye mark, spare, dose, printer, alignment
B	8	35.06		5,436.59	8,372.0	2,935.41		Dose, clutch, three-way valve, sachet cognates
C	1	24.83		6,293.27	8,372.0	2,078.73		Vertical leakage, eye mark
D	7	32.46		5,654.34	8,372.0	2,717.66		Horizontal leakage, knife, sachet cognates, dose
E	4	29.82		5,875.27	8,372.0	2,496.73		Printer, sealing temperature
F	9	42.77		4,791.45	8,372.0	3,580.55		vertical leakage, jaw
G	5	30.83		5,790.76	8,372.0	2,581.24		Knife, seal, gasket
H	5	30.83		5,790.76	8,372.0	2,581.24		Knife, alignment
I	2	27.17		6,097.17	8,372.0	2,274.83		Printer, alignment
J	2	27.17		6,097.17	8,372.0	2,274.83		Knife, eye mark
Total		66.01	500	55,266	83,720	28,454	1000	28,454.00

Source: - technical & production manager, data analyzer, and team leader, SCAND, logbook.

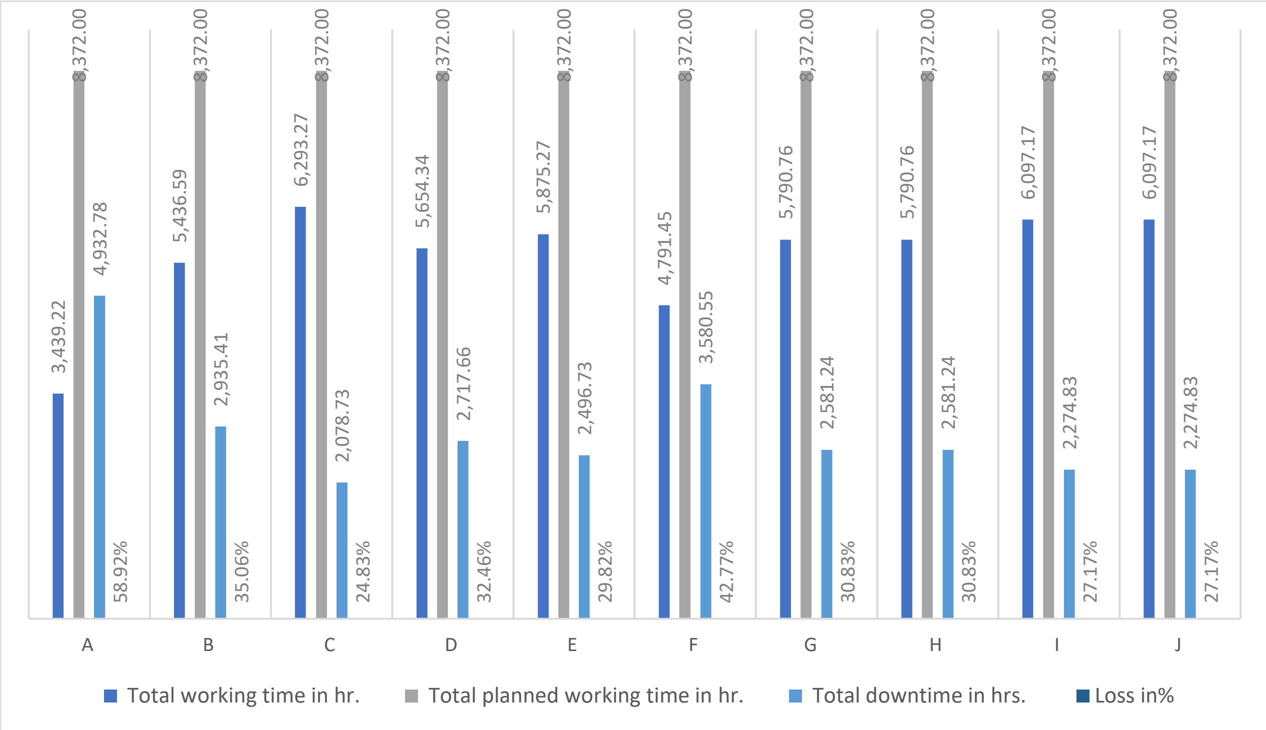


Figure 4.9 Filler and packaging machine working time, planned time and downtime status

This cluster chart shows the relation and comparison of each machine type, single and double-type filler machines, in terms of planned time, working time, and downtime with respect to loss in percentage.

The availability of the above table filler and packaging machine is fulfilled by the following: mathematical calculation

$$\text{Availability filler and pckaging}$$

$$= \frac{\text{actual available time filler and pckaging i}}{\text{planned available time filler and pckaging i}} \text{(from equ 2.1)}$$

$$= \frac{\text{Total working time of filler and pckaging machine i}}{\text{Total Planned working time filler and pckaging machine i}}$$

Were:

Machine: single and double type filler and packaging machines, single type namely A, B, C, D, E, and F, and double type namely G & H, I & J.

Section IV (Finishing and processing zone)

$$\text{Availabilty of filler and pckaging A} = \frac{\text{Total working time of filler and pckaging A}}{\text{Total Planned working time filler and pckaging A}}$$

$$= \frac{3439.22\text{hr}}{8372\text{hr}}$$

$$= 0.4108 = 41.08\%$$

$$\text{Availabilty of filler and pckaging B} = \frac{\text{Total working time of filler and pckaging B}}{\text{Total Planned working time filler and pckaging B}}$$

$$= \frac{5436.59\text{hr}}{8372\text{hr}}$$

$$= 0.6494 = 64.94\%$$

$$\text{Availabilty of filler and pckaging C} = \frac{\text{Total working time of filler and pckaging C}}{\text{Total Planned working time filler and pckaging C}}$$

$$= \frac{6293.27\text{hr}}{8372\text{hr}}$$

$$= 0.7517 = 75.17\%$$

$$\text{Availabilty of filler and pckaging D} = \frac{\text{Total working time of filler and pckaging D}}{\text{Total Planned working time filler and pckaging D}}$$

$$= \frac{5654.34\text{hr}}{8372\text{hr}}$$

$$= 0.6754 = 67.54\%$$

$$\text{Availabilty of filler and pckaging E} = \frac{\text{Total working time of filler and pckaging E}}{\text{Total Planned working time filler and pckaging E}}$$

$$= \frac{5875.27\text{hr}}{8372\text{hr}}$$

$$= 0.7018 = 70.18\%$$

$$\text{Availabilty of filler and pckaging F} = \frac{\text{Total working time of filler and pckaging F}}{\text{Total Planned working time filler and pckaging F}}$$

$$= \frac{4791.45\text{hr}}{8372\text{hr}}$$

$$= 0.5723 = 57.23\%$$

$$\text{Availabilty of filler and pckaging G} = \frac{\text{Total working time of filler and pckaging G}}{\text{Total Planned working time filler and pckaging G}}$$

$$= \frac{5790.76\text{hr}}{8372\text{hr}}$$

$$= 0.6917 = 69.17\%$$

$$\text{Availabilty of filler and pckaging H} = \frac{\text{Total working time of filler and pckaging H}}{\text{Total Planned working time filler and pckaging H}}$$

$$= \frac{5790.76\text{hr}}{8372\text{hr}}$$

$$= 0.6917 = 69.17\%$$

$$\text{Availabilty of filler and pckaging I} = \frac{\text{Total working time of filler and pckaging I}}{\text{Total Planned working time filler and pckaging I}}$$

$$= \frac{6097.17\text{hr}}{8372\text{hr}}$$

$$= 0.7283 = 72.83\%$$

$$\text{Availabilty of filler and pckaging J} = \frac{\text{Total working time of filler and pckaging J}}{\text{Total Planned working time filler and pckaging J}}$$

$$= \frac{6097.17\text{hr}}{8372\text{hr}}$$

$$= 0.7283 = 72.83\%$$

The filler and packaging machine downtime is essential for identifying the priority of the losses compared to other fundamental losses. This is used to know the priority issues that are against the enhancement of the machine's availability.

Table 4.10 Pareto table of filler and packaging machine availability

Filler and Packaging	Total downtime (in hr.)	Cumulative	Percentage	Cumulative Percentage
A	4,932.78	4,932.78	17.34%	17.34%
F	3,580.55	8,513.33	12.58%	29.92%
B	2,935.41	11,448.74	10.32%	40.24%
D	2,717.66	14,166.40	9.55%	49.79%
G	2,581.24	16,747.64	9.07%	58.86%
H	2,581.24	19,328.88	9.07%	67.93%
E	2,496.73	21,825.61	8.77%	76.70%
I	2,274.83	24,100.44	7.99%	84.70%
J	2,274.83	26,375.27	7.99%	92.69%
C	2,078.73	28,454.00	7.31%	100.00%

From this Pareto table prepared Pareto chart

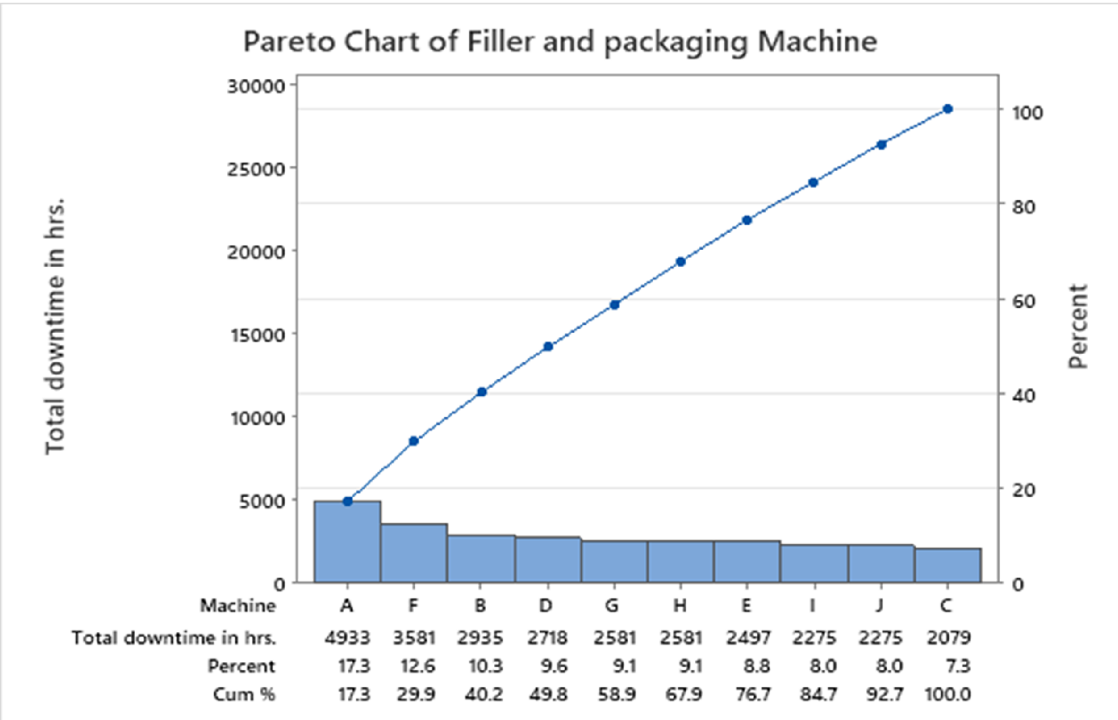


Figure 4.10 Pareto chart of filler and packaging machines downtime

Based on the data provided, here are the basic ideas for the Pareto table of filler and packaging machine availability:

The above Pareto chart shows that the downtime data for 10 filler and packaging machines labeled A through J. Machine A had the highest total downtime of 4,932.78 hours, accounting for 17.34% of the total downtime (28,454 hours). Machine F had the second highest downtime of 3,580.55 hours (12.58% of total).

The cumulative percentage column shows that the top 5 machines (A through E) contributed around 76.7% of the total downtime, indicating that focusing efforts on improving these machines could significantly reduce overall downtime.

As shown in the above figure 4.11, all filler machines are related to downtime. A machine's significant downtime register, which is almost 58.92% availability losses, is resisted. Due to this and the likelihood of machine A, which is machine F, the plant registers more downtime. The below pie chart also shows

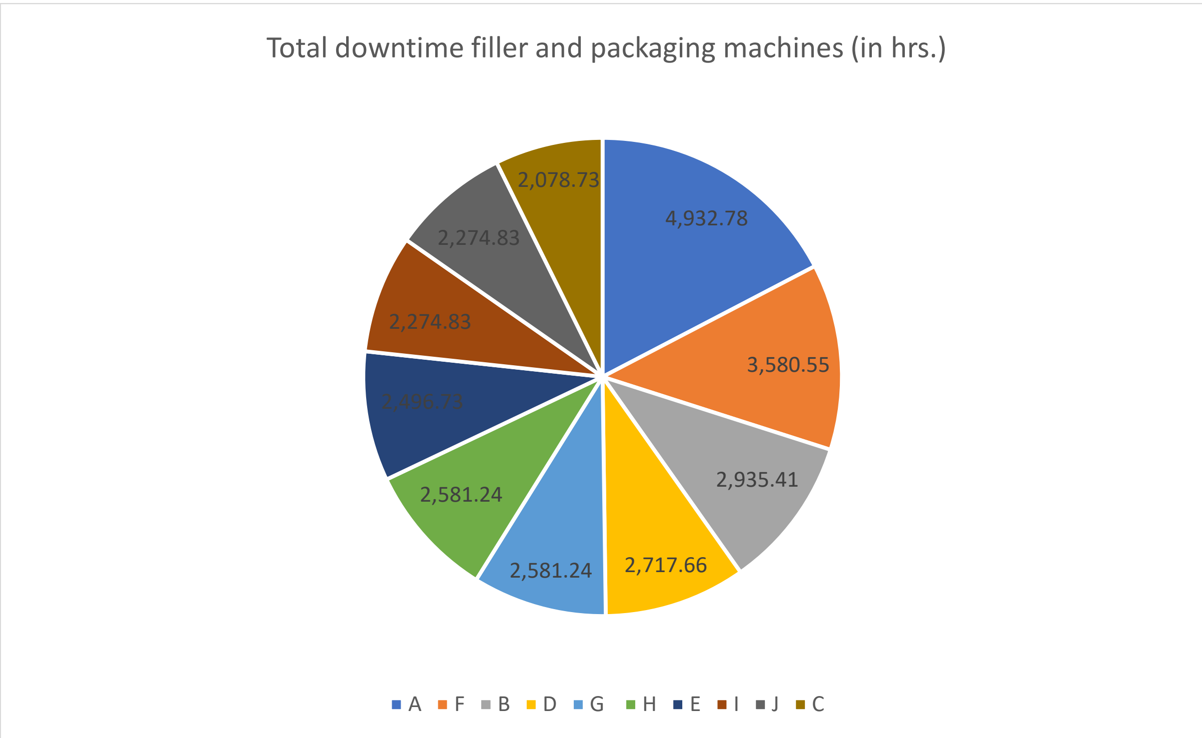


Figure 4.11 Pie chart representation of filler and packaging machines downtime

The reasons for downtime listed for each machine include issues like leakages, dosing problems, valve and clutch faults, printer and sealing issues, knife problems, etc. These reasons provide pointers to the specific parts, components, and processes that need to be optimized for each machine to improve availability.

In a run chart, data is plotted over time along with control limits. Each data point filler and packaging machine represents the total working time or downtime for a machine.
The chart would show colored lines, one for each machine, with data points plotted for each reporting period. The Y axis would show the total working time or downtime in hours, while the X axis represents the reporting period – perhaps in year. Each data point shows the total time for that machine in that period.
By plotting the data over time in a run chart, you can potentially identify non-random variation and trends in filler and packaging machine availability. Anomalies like increases or decreases in total time or downtime for a machine would stand out visually. Also compare the performance of each filler and packaging machine over time to assess differences in consistency.
To know the pattern of the big data on filler and packaging machines from real nonrandom behavioral big data sources on tip-track machines, we used a run chart. This chart was used to predict the future pattern by analyzing it. So, the run chart of filler and packaging machine pattern trends is expressed in the below chart.

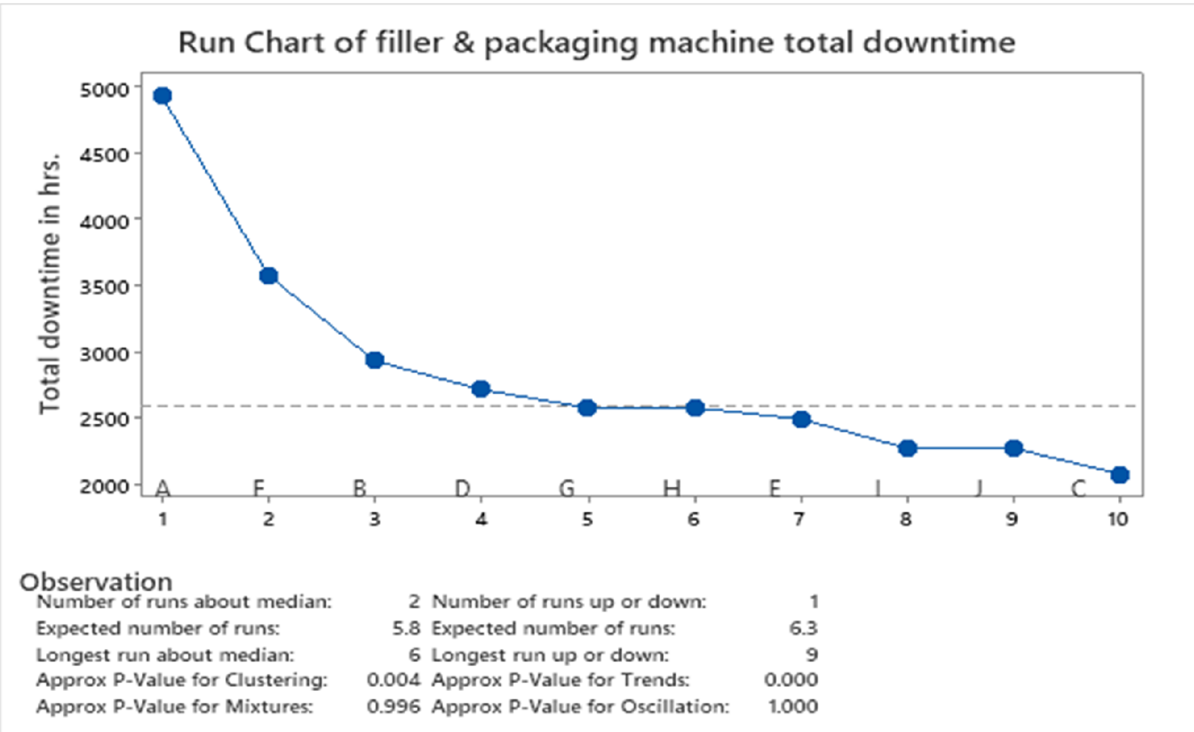


Figure 4.12 Run chart of filler and packaging machine downtime

From this, the manufacturing industry can discover areas for improvement and take specific actions to increase equipment dependability and uptime by monitoring availability data and trend analysis over time. Determine the main causes of availability losses by combining data analysis approaches with reliability engineering methodologies. Then, take specific steps to enhance overall equipment performance and decrease downtime.

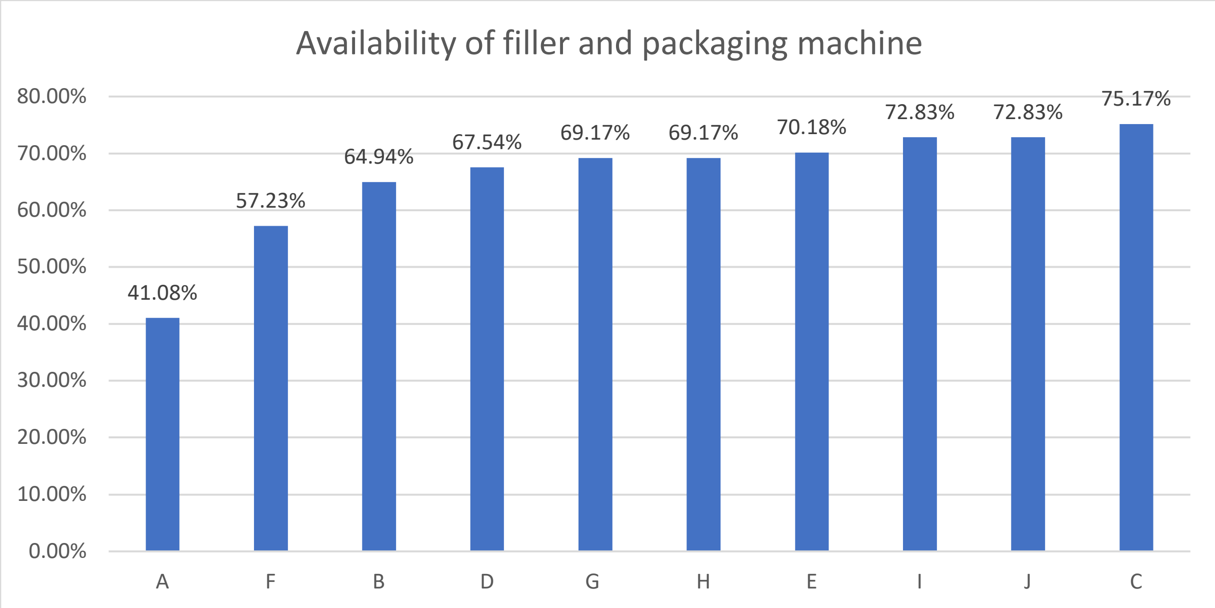


Figure 4.13 Availability cluster chart of filler and packaging machine

Therefore, from the above table consideration from selected season the availability trend will be proceed in this way, so availability of these factor we can calculated depend on the below table 4.11

Table 4.11 Summary table for auxiliary and filler and packaging machine

Time in hours for each auxiliary machine from (January to May 2023)					
For 364day = 23 hr. per day 8372hr.	Total downtimes	Total Planned downtimes	Total unplanned downtimes	Total working time	Total planned working time
	28,454.00	15,865.46	12,588.54	55,266.00	83,720.00

Time in hours for each 10 filler & packaging machines (A, B, C, D, E, F, G, H, I, J) in 2022					
For 364day = 23hr. Per day= 8372hr	Total downtimes	Planned downtimes	Unplanned downtimes	Total working time	Total planned working times
	28,454.00	15,865.46	12,588.54	55,266.00	83,720.00

Source: - technical & production manager, data analyzer, and team leader, SCAND, logbook.

$$\text{Availability} = \frac{\text{actual available time}}{\text{planned available time}} \ldots \ldots \ldots .\text{(from equ 2.1)}$$

$$\text{Availability auxilary machine} = \frac{\text{actual available time}}{\text{planned available time}}$$

$$= \frac{58130.15}{66976}$$

$$= 0.8679$$

$$= 86.79\%$$

$$\text{Availability filler \& packaging} = \frac{Total\ working\ time}{Total\ Planned\ working\ time}$$

$$= \frac{55,266.00}{83,720.00}$$

$$= 0.66$$

$$= 66.01\%$$

4.3.2.2 Cause and effect diagram of filler and packaging machine availability losses

The potential cause of the problem of the largest downtime, that is, the lowest availability in all over the auxiliary machines, especially filler and packaging machines, is expressed on the following fishbone diagram. Based on the data provided in tables 4.7 and 4.9, the problem at hand is the availability of filling and packaging on each filler, and the data shows that there are various causes for the downtime of each machine. The fishbone diagram would show the main categories of causes, such as people, processes, equipment, materials, and the environment. These categories would then branch out into more specific causes for each machine.

Under the equipment category, the causes for downtime could include issues with the vertical and horizontal leakage and seal, eye mark, raw material, dose, printer, alignment, clutch, three-way valve, sachet cognates, sealing temperature, knife, and seal are known. This information would be displayed on the fish bone diagram, with each cause branching out from the main categories.

In general, analyzing the causes of filler and packaging machine failure highest downtime and lowest availability using a fish-bone diagram help identify the root causes and take corrective actions to improve the performance and reliability of the filler and packaging machine in Hilina manufacturing industry.

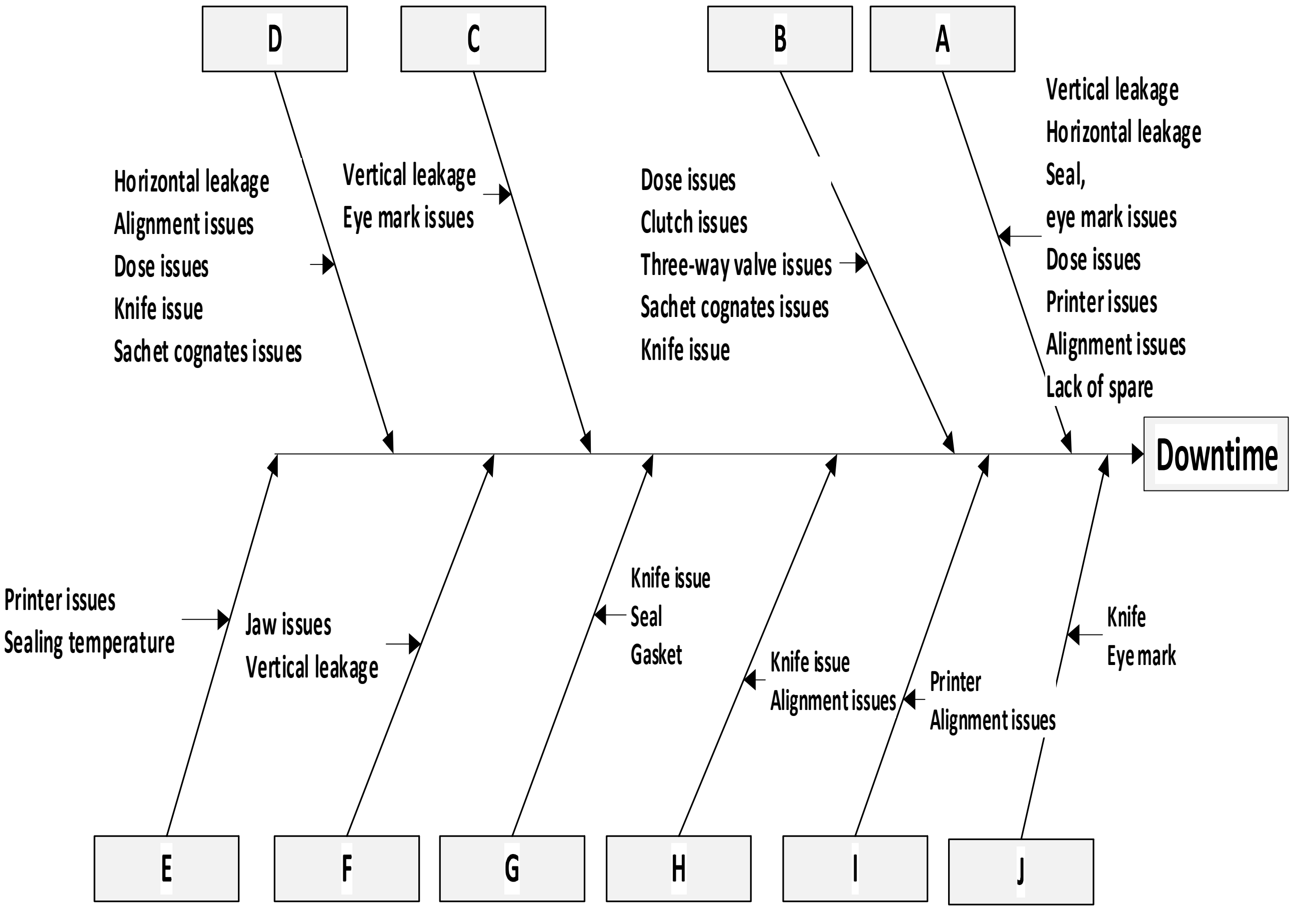


Figure 4.14 Fishbone diagram of filler and packaging machines in accordance to high downtime

4.3.3 Performance losses trend analysis and findings

The specific reasons for the losses determine the fundamental causes of the performance loss trend in Hilina's manufacturing organization. Equipment failure, ineffective maintenance procedures, ineffective manufacturing procedures, and insufficient personnel training are some of the basic, widespread core causes (RC) of performance losses in the manufacturing industry. Through analyzing data on important performance measures, such as OEE, and using tools like cluster chart, pie chart, Pareto charts, run charts, and root cause analysis approaches, identify the accurate root causes of performance losses.

Once the underlying causes are known, specific remedies can be developed and put into action to enhance worker training, decrease downtime, and improve equipment performance. By applying these actions, manufacturing operations became more effective overall, and performance losses were minimized. On the Hilina manufacturing process, the auxiliary or fundamental machines have been selected to enhance OEE since most performance losses happen on these machines.

Table 4.12 Performance of auxiliary grand machines

The overall operation or production speed from January to December 2022					
Equipment	Design capacity speed (in kg/hr.)	Actual speed (in kg/hr.)	Speed losses (in kg/hr.)	Performance (in %)	Reason
Roaster machine	4368000	4190222.4	177777.6	95.93%	Hull, moisture
Sortex machine	4368000	4180612.87	187387.13	95.71%	Camera lens
Pre-Blend machine	4368000	4089321.95	278678.05	93.62%	Tune, cleaning
Grinder & Mixer A	4368000	4004145.65	363854.35	91.67%	Brushes, satire
Blend machine	4368000	4103299.27	264700.73	93.94%	Tune, cleaning
Grinder & Mixer B	4368000	3991915.73	376084.27	91.39%	Brushes, satire
Vacuum pump	4368000	4146105.58	221894.42	94.92%	Mechanical seal
Thermal treatment	4368000	4181049.63	186950.37	95.72%	Pneumatic, thermal sensor
Total	34944000	32886673.08	2057326.92	94.11%	
Filler & packaging	2508000	1378057.8	1242742.2	54.95%	Printer, eye mark, three-way valve, knife, alignment, dose
Total	37452000	34264730.88	3300069.12	91.49%	

Source: - technical & production manager, data analyzer, and team leader, SCAND, logbook

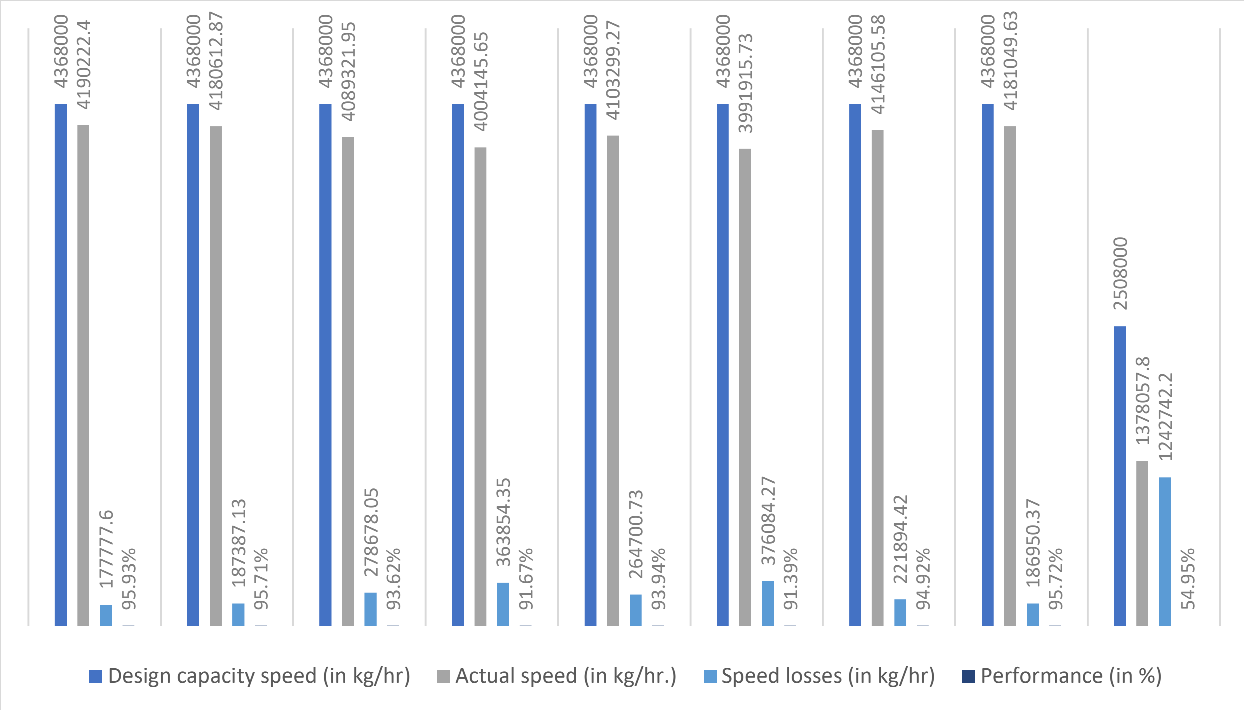


Figure 4.15 Performance of auxiliary grand machines

The mathematical analysis of auxiliary grand machine performance

$$\text{Performance of machine i} = \frac{\text{Actual production time machine i}}{\text{planned production time machine i}} \dots\dots\dots (from\ equ\ 2.4)$$

$$= \frac{\text{Actual speed machine i}}{\text{Design capacity speed machine i}}$$

Were:

Machine i= roaster, Sortex, pre-blend, blend, grinder and mixer A & B, vacuum pump, thermal treatment

Section I (Filtering raw material zone)

$$\text{Performance of roaster machine} = \frac{\text{Actual speed roaster machine}}{\text{Design capacity speed roaster machine}}$$

$$= \frac{4190222.4\text{kg/hr}}{4368000\text{kg/hr}}$$

$$= 0.9563$$

$$\text{Performance of Sortex machine} = \frac{\text{Actual speed Sortex machine}}{\text{Design capacity speed Sortex machine}}$$

$$= \frac{\frac{4180612.87\text{kg}}{\text{hr}}}{\frac{4368000\text{kg}}{\text{hr}}}$$

$$= 0.9571$$

Section II & III (Sorting and Production zone)

$$\text{Performance of pre blend machine} = \frac{\text{Actual speed roaster machine}}{\text{Design capacity speed roaster machine}}$$

$$= \frac{\frac{4089321.95.4\text{kg}}{\text{hr}}}{\frac{4368000\text{kg}}{\text{hr}}}$$

$$= 0.9362$$

$$\text{Performance of grinder\&mixer machine A} = \frac{\text{Actual speed grinder \& mixer A}}{\text{Design capacity speed grinder \& mixer A}}$$

$$= \frac{\frac{4004145.65\text{kg}}{\text{hr}}}{\frac{4368000\text{kg}}{\text{hr}}}$$

$$= 0.9167$$

$$\text{Performance of blend machine} = \frac{\text{Actual speed blend machine}}{\text{Design capacity speed blend machine}}$$

$$= \frac{4103299.27\text{kg/hr}}{4368000\text{kg/hr}}$$

$$= 0.9394$$

$$\text{Performance of grinder\&mixer machine B} = \frac{\text{Actual speed grinder \& mixer B}}{\text{Design capacity speed grinder \& mixer B}}$$

$$= \frac{\frac{3991915.73\text{kg}}{\text{hr}}}{\frac{4368000\text{kg}}{\text{hr}}}$$

$$= 0.9139$$

$$\text{Performance of vaccum pump machine} = \frac{\text{Actual speed vaccum pump}}{\text{Design capacity speed vaccum pump}}$$

$$= \frac{\frac{4146105.58\text{kg}}{\text{hr}}}{\frac{4368000\text{kg}}{\text{hr}}}$$

$$= 0.9139$$

$$\text{Performance of thermal treatment machine} = \frac{\text{Actual speed thermal treatment}}{\text{Design capacity speed thermal treatment}}$$

$$= \frac{436800\text{kg/hr}}{4368000\text{kg/hr}}$$

$$= 0.9572$$

Section IV (Finishing and processing zone)

$$\text{Performance filler and packaging machine} = \frac{\text{Actual speed filler and packaging}}{\text{Design capacity speed filler and packaging}}$$

$$= \frac{1378057.8}{250800}$$

$$= 0.5795$$

The data provided, and its calculation, the total actual speed attained from January to December 2022 is 91.49% of the total design capacity speed. This indicates an overall performance loss or speed loss of 8.51%.

The largest speed losses seem to be occurring at the Filler & packaging machine, with an actual speed of only 54.95% of design capacity. This suggests the Filler & packaging machine is the major source of performance loss. Reasons listed for this machine include issues with the printer, eye mark, three-way valve, knife and misalignment.

Other machines with high-speed losses include the Pre-Blend machine (6.38% loss) and Grinder & Mixer A (8.33% loss). The reasons listed for these losses are tunning and cleaning issues as well as issues with the brushes and satire.

Filler & packaging machine components as well as tunning, cleaning and component issues for some of the other machines. Focusing on resolving these issues could help improve the overall production speed.

Based on the figure and discussion in the above figure 4.15, it seems the diagram shows the performance of an auxiliary machine across different categories: design capacity speed, actual speed, and speed losses. The order of significant speed losses is tiny.

To identify the significant performance losses for the auxiliary machine, need more details on the figure and calculations mentioned in the above table 4.12. However, in general, to determine performance losses of a machine:

- Compare the design capacity speed with the actual speed. The difference indicates losses due to friction and mechanical resistance.
- Identify the different sources of losses - mechanical friction, electrical resistance, dynamic drag, etc. Prioritize them based on their contribution to the total losses.
- Calculate the total efficiency of the machine based on actual output versus design capacity. The complement of efficiency indicates total losses.

On the above figure 4.13, it shows that the performance value of an auxiliary grand machine is compared across a few categories, which are the design capacity speed of the machine, the actual speed of the machine, and its speed losses. In this diagram, the order and priority of significant losses are negligible. In order to know the significant performance losses or speed losses of the auxiliary machine across each value, use the Perot chart shown below figure 4.17.

The basic idea is to represent the speed losses (in kg/hr) of in grand auxiliary machines in a production line using a combination of a pie chart, Pareto chart, and a discussion on the idea.

The discussion focuses on analysing the results obtained from the pie chart and Pareto chart. It can highlight the grand auxiliary machines that contribute the most to the speed losses and discuss potential actions to address the issues. The aim is to identify the key machines causing the majority of the losses and prioritize them for improvement measures, such as maintenance, optimization, or replacement. By combining the visual representation of the pie chart and the Pareto chart, along with a detailed discussion, the idea provides a comprehensive understanding of the distribution of speed losses and aids in decision-making for optimizing the production line.

Table 4.13 Pareto table for auxiliary grand machine performance

Auxiliary grand machine	Speed losses (in kg/hr.)	Performance (in %)	cumulative	percentage	Cumulative percentage
Filler & packaging	1242742.2	54.95%	1242742	37.66%	37.66%
Grinder & Mixer B	376084.27	91.39%	1618826	11.40%	49.05%
Grinder & Mixer A	363854.35	91.67%	1982681	11.03%	60.08%
Pre-Blend machine	278678.05	93.62%	2261359	8.44%	68.52%
Blend machine	264700.73	93.94%	2526060	8.02%	76.55%
Vacuum pump	221894.42	94.92%	2747954	6.72%	83.27%

Sortex machine	187387.13	95.71%	2935341	5.68%	88.95%
Thermal treatment	186950.37	95.72%	3122292	5.67%	94.61%
Roaster machine	177777.6	95.93%	3300069	5.39%	100.00%

The table presents the speed losses in kilograms per hour and the performance percentage of each machine. The cumulative percentage column indicates the total contribution of each machine to the overall performance of the production process. The table helps identify which machines are causing the most significant speed losses and lower performance, allowing for targeted improvements to increase the efficiency of the production process.

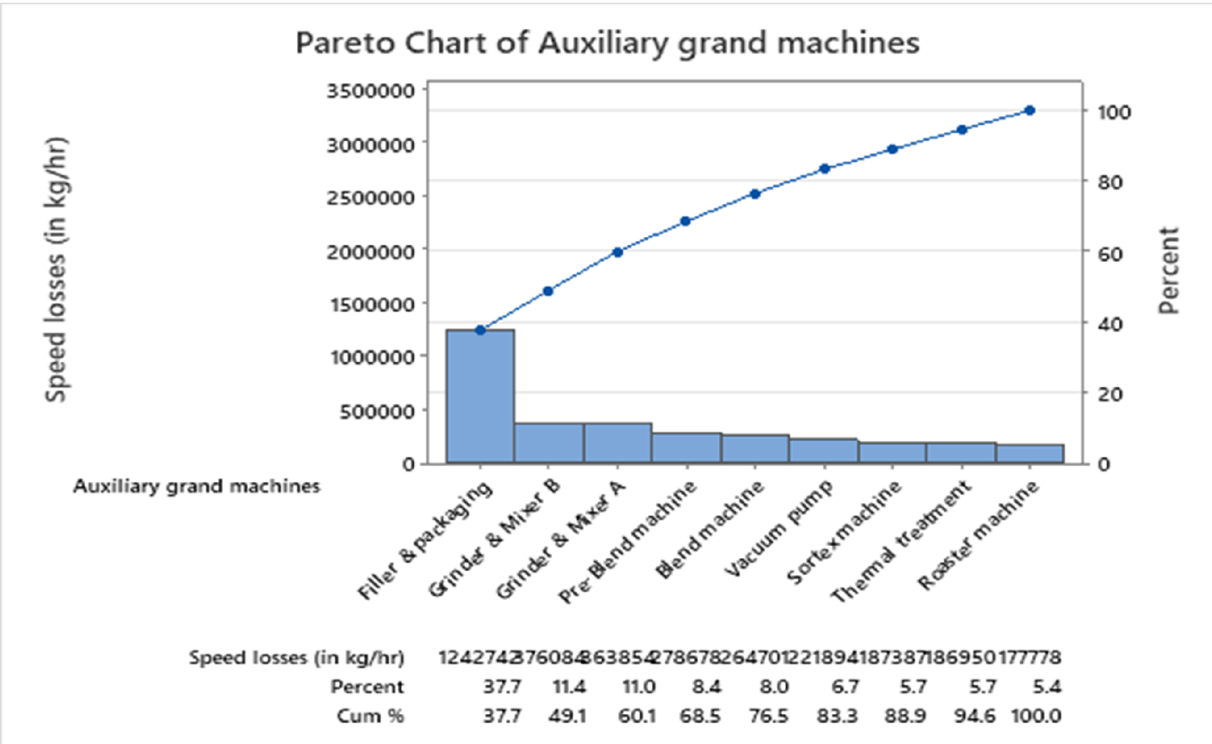


Figure 4.16 Pareto chart of auxiliary grand machines performance

Based on the data in the Pareto table 4.13 and figure 4.17, the following components have the largest impact on speed losses and should be priorities for improving the auxiliary grand machine performance:

- Filler & packaging machine has the highest speed losses at 54.95% and should be the initial focus for optimization. Reducing losses in this stage could potentially yield the greatest benefit.

- Grinder & Mixer B has the second highest speed losses at 91.39% and should also be evaluated for potential improvements.

Components with lower speed losses like Roaster machine and Thermal treatment should likely have a lower optimization priority because their relative impacts are smaller.

In general, following a Pareto analysis approach of focusing on the components with the greatest impact first can yield the most effective performance improvements. The data shows that addressing the top 3-4 components could result in over 80-90% of the potential gains.

In addition of Pareto, combining with pie chart can visually represent the cumulative contribution and individual speed losses for auxiliary grand machine.

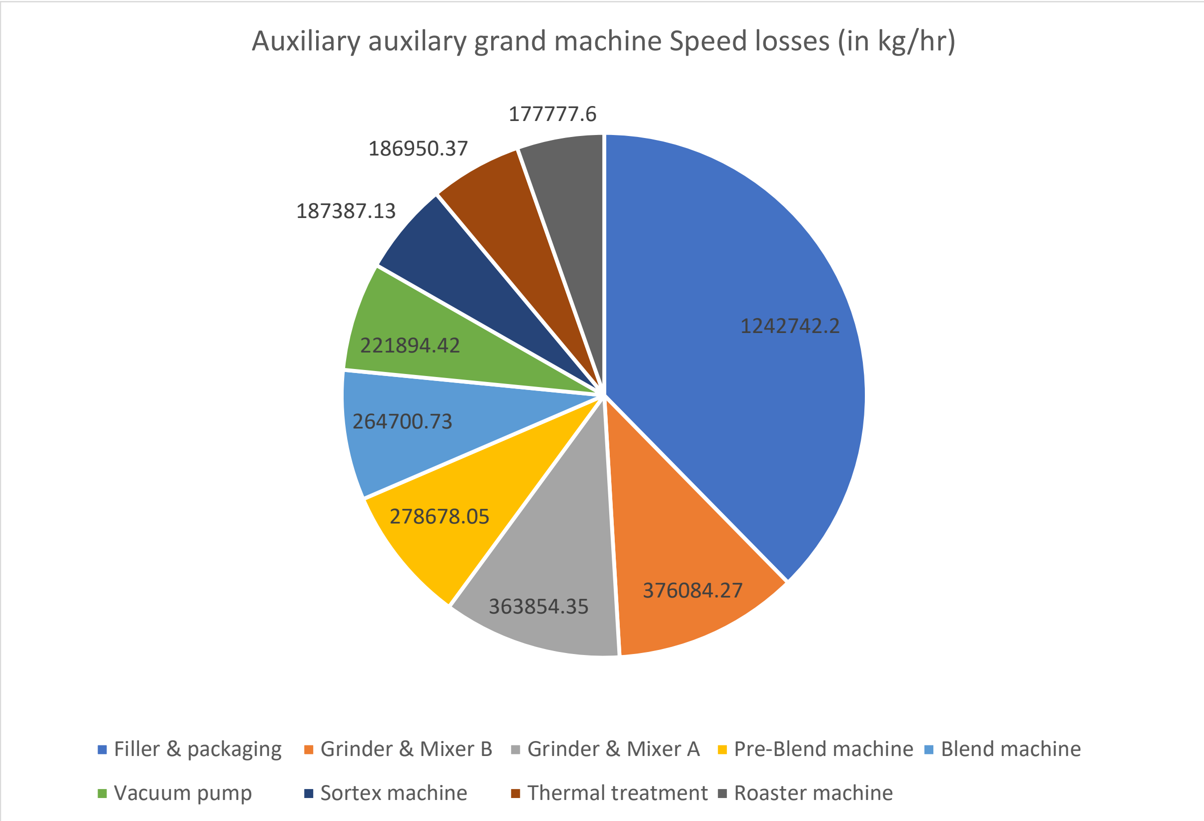


Figure 4.17 Auxiliary grand machine Speed losses

A pie chart can be created to visually represent the distribution of speed losses among the grand auxiliary machines. Each machine's speed loss value converted into a percentage of the total speed losses. The resulting pie chart show the proportional contribution of each machine to the overall speed losses. While Pareto chart: arranges the machines in descending order based on their speed losses. The chart has two axes, with the filler machines listed on the horizontal axis and the speed losses on the vertical axis. The bars arranged in descending order, and a cumulative percentage line will be added to show the cumulative contribution of each machine to the total speed losses.

By plotting the data over time in a run chart, potentially identify non-random variation and trends in auxiliary machine performance. Anomalies like increases or decreases in total time or downtime for a machine would stand out visually. Also compare the performance of each auxiliary grand machine over time to assess differences in consistency. To know the pattern of the big data on auxiliary grand machine from real nonrandom behavioral big data sources on tip-track machines, we used a run chart. This chart was used to predict the future pattern by analyzing it. So, the run chart of auxiliary grand machine pattern trends is expressed in the below chart.

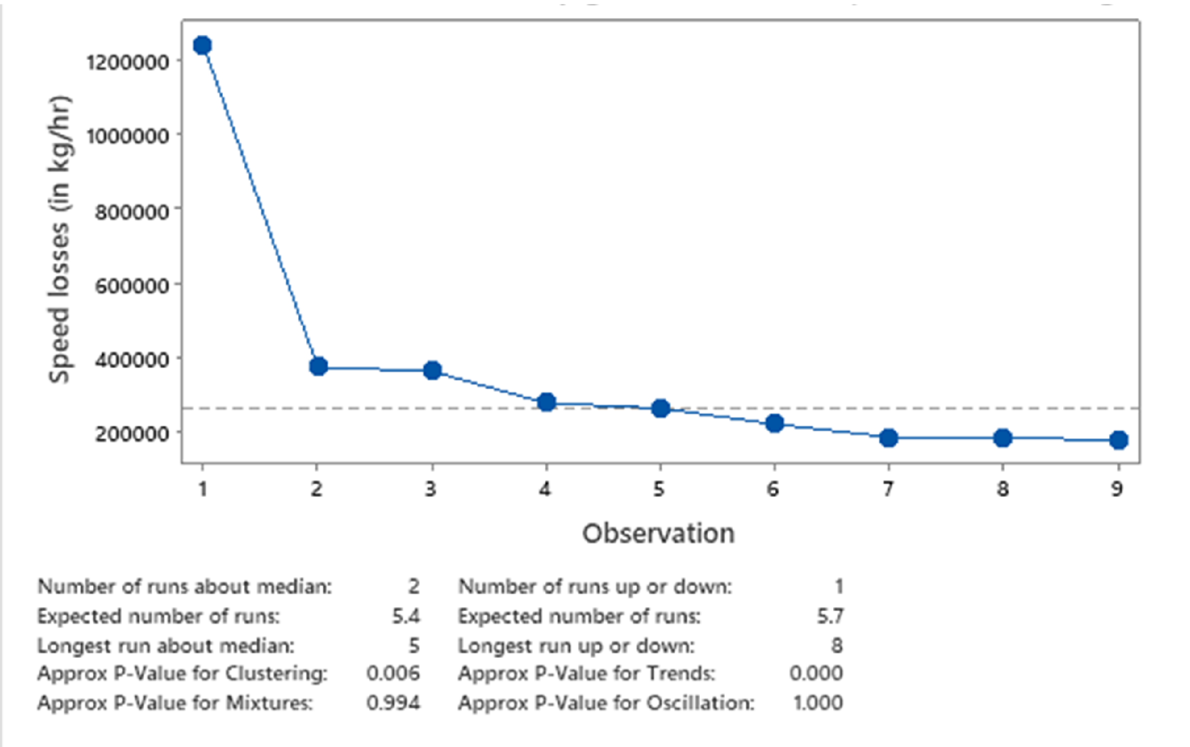


Figure 4.18 Run chart of auxiliary grand machine performance

From this, the manufacturing industry can discover areas for improvement and take specific actions to increase equipment dependability and uptime by monitoring speed data and trend analysis over time. Determine the main causes of speed losses by combining data analysis approaches with reliability engineering methodologies. Then, take specific steps to enhance overall equipment performance and decrease speed losses.

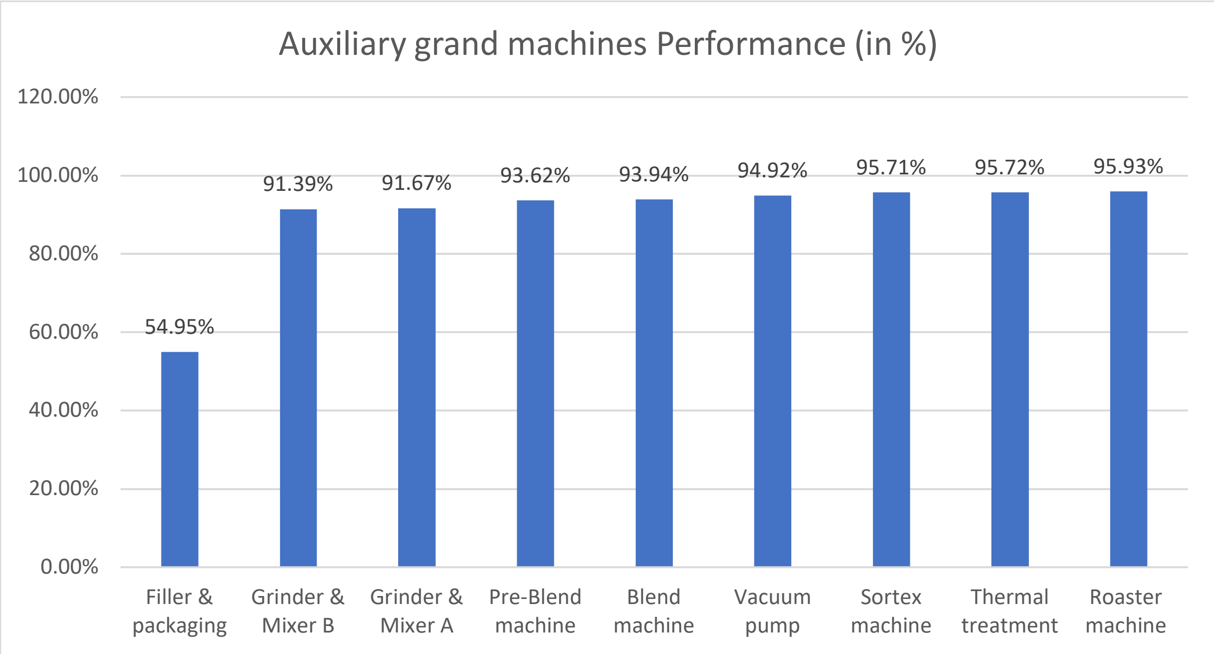


Figure 4.19 Auxiliary grand machines performance

4.3.3.1 Cause and effect diagram auxiliary grand machine performance losses

The potential cause of the problem of the lowest speed or speed losses, that is, the lowest performance in all over the auxiliary grand machines, is expressed on the following fishbone diagram. Based on the data provided in tables 4.12 and 4.13, the problem at hand is the performance of auxiliary grand machine, and the data shows that there are various causes for the speed loses of each machine. The fishbone diagram would show the main categories of causes, such as people, processes, equipment, materials, and the environment. These categories would then branch out into more specific causes for each machine.

Under the equipment category, the causes for speed losses could include various issues, such as performance and age of machine, labor performance, and other. This information would be displayed on the fish bone diagram, with each cause branching out from the main categories.

By investigate the factors contributing to the speed losses in the overall operation or production from January to December 2022, prepared the fishbone diagram, which is inter-relation of cause-and-effect of the fundamental speed loss or performance losses of auxiliary machine.

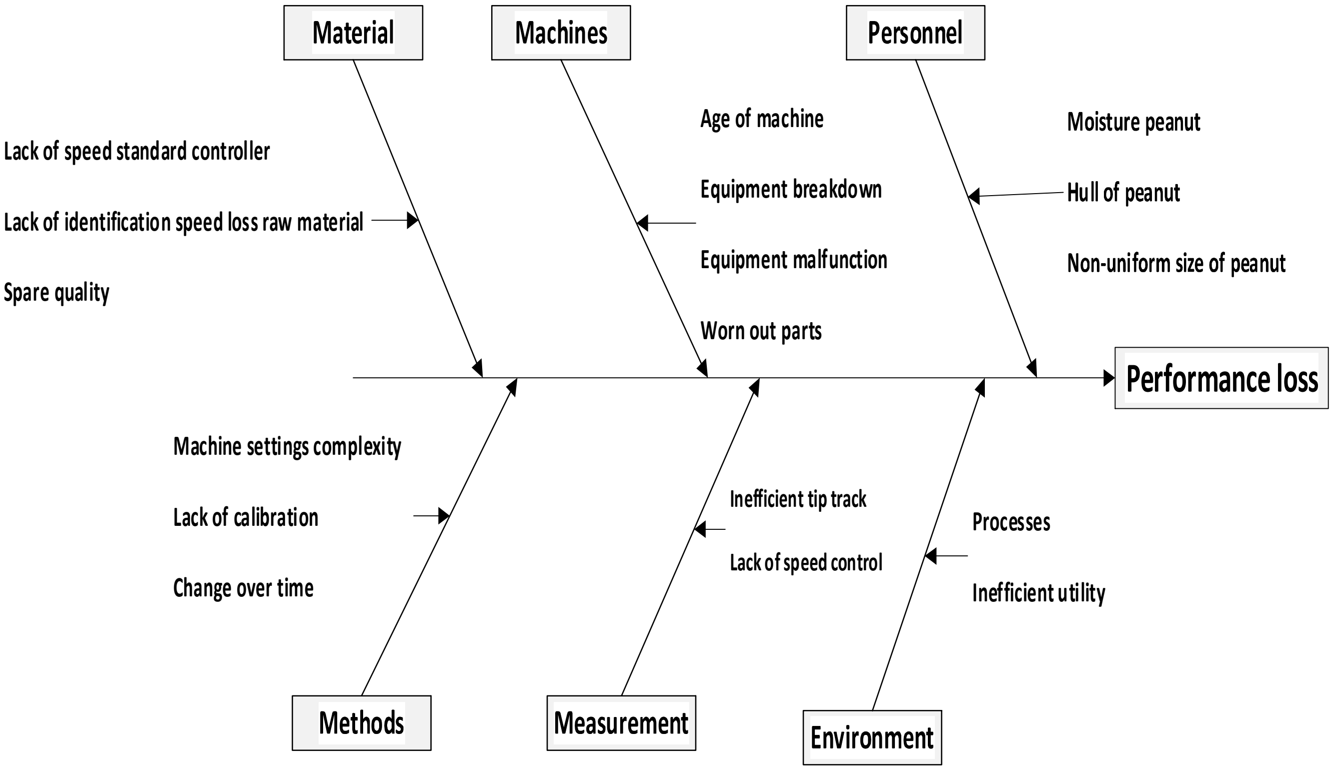


Figure 4.20 Cause-and-effect diagram of auxiliary grand machine in accordance of speed losses

This diagram provides a visual representation of the possible causes contributing to the production speed losses, allowing for further analysis and problem-solving. It can assist in identifying areas of improvement and guiding efforts to increase overall production efficiency.

On the above performance analysis of all over-auxiliary grand machines, it gives significant emphasis to the filler and packaging machine because this has the highest speed losses at 54.95% and should be the initial focus for optimization. Reducing losses at this stage could potentially yield the greatest benefit. Separate analyses are provided in Table 4.14 below to investigate the filler and packaging machine's major performance losses.

Table 4.14 Performance of filler & packaging on each device

Selected machine which is very big performance difference from January to December 2022					
Equipment	Design capacity speed (in kg/hr.)	Actual Speed (in kg/hr.)	Speed losses (in kg/hr.)	Speed loss in %	Reason of speed losses
A	313500	145608	167892	53.55	Vertical & horizontal leakage & seal, eye mark, dose, printer, alignment
B	313500	175230	138270	44.11	Dose, clutch, three-way valve, sachet cognates
C	313500	195042	118458	37.79	Vertical leakage, eye mark
D	313500	111349.8	202150.2	64.48	Horizontal leakage
E	313500	189546	123954	39.54	Printer, sealing temperature
F	313500	188778	124722	39.78	vertical jaw leakage
G & H	313500	186252	127248	40.59	Knife, seal, alignment, eye mark
I & J	313500	186252	127248	40.59	Printer, alignment, knife
Total	2508000	1378057.8	1129942.2	45.05	

Source: - technical & production manager, data analyzer, and team leader, SCAND, logbook.

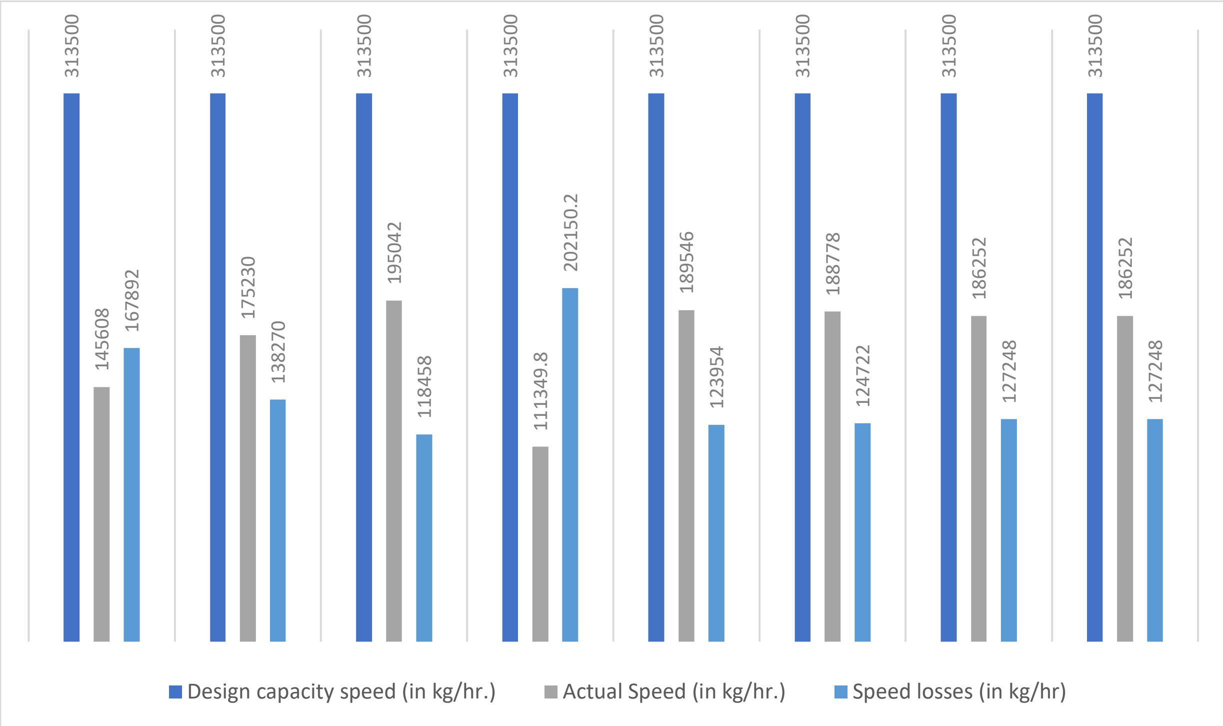


Figure 4.21 Performance chart of filler & packaging

The mathematical analysis of filler and packaging machine performance

Section IV (Finishing and processing zone)

$$\text{Performance of machine i} = \frac{\text{Actual production time machine i}}{\text{planned production time machine i}} \dots\dots\dots (from\ equ\ 2.4)$$

$$= \frac{\text{Actual speed machine i}}{\text{Design capacity speed machine i}}$$

Were:

Machine i= filler and packaging machine A, B, C, D, E, F, G & H, I & J

$$\text{Performance filler and packaging machine A} = \frac{\text{Actual speed filler and packaging A}}{\text{Design capacity speed filler and packaging A}}$$

$$= \frac{145608\text{kg/hr}}{313500}$$

$$= 0.4645$$

$$= 46.45\%$$

$$\text{Performance filler and packaging machine B} = \frac{\text{Actual speed filler and packaging B}}{\text{Design capacity speed filler and packaging B}}$$

$$= \frac{175230\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.5589$$

$$= 55.89\%$$

$$\text{Performance filler and packaging machine C} = \frac{\text{Actual speed filler and packaging C}}{\text{Design capacity speed filler and packaging C}}$$

$$= \frac{195042\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.6221$$

$$= 62.21\%$$

$$\text{Performance filler and packaging machine D}$$

$$= \frac{\text{Actual speed filler and packaging D}}{\text{Design capacity speed filler and packaging D}}$$

$$= \frac{11349.8\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.3552$$

$$= 35.52\%$$

$$\text{Performance filler and packaging machine E} = \frac{\text{Actual speed filler and packaging E}}{\text{Design capacity speed filler and packaging E}}$$

$$= \frac{189546\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.6046$$

$$= 60.46\%$$

$$\text{Performance filler and packaging machine C} = \frac{\text{Actual speed filler and packaging C}}{\text{Design capacity speed filler and packaging C}}$$

$$= \frac{188778\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.6022$$

$$= 60.22\%$$

$$\text{Performance filler and packaging G \& H} = \frac{\text{Actual speed filler and packaging G \& H}}{\text{Design capacity speed filler and packaging G \& H}}$$

$$= \frac{186252\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.5941$$

$$= 59.41\%$$

$$\text{Performance filler and packaging I \& J} = \frac{\text{Actual speed filler and packaging I \& J}}{\text{Design capacity speed filler and packaging I \& J}}$$

$$= \frac{186252\text{kg/hr}}{313500\text{kg/hr}}$$

$$= 0.5941$$

$$= 59.41\%$$

The filler and packaging machine speed loss is essential for identifying the priority of the losses compared to other fundamental losses. This is used to know the priority issues that are against the enhancement of the machine's performance. Pareto analysis is required to determine which machines are given priority among these.

Table 4.15 Pareto table of filler and packaging machine performance

Equipment	Cumulative	Percentage	Cumulative percentage
D	202150.2	17.89%	17.89%
A	370042.2	14.86%	32.75%
B	508312.2	12.24%	44.99%
G and H	635560.2	11.26%	56.25%
I and J	762808.2	11.26%	67.51%
F	887530.2	11.04%	78.55%
E	1011484	10.97%	89.52%
C	1129942	10.48%	100.00%

The table shows the cumulative percentage of filler and packaging machines' performance over the given time period. The machine D has a performance of 202,150.2 which constitutes 17.89% of the overall performance losses. Similarly, machine A has a performance of 370,042.2 which makes up 14.86% of the total performance losses. The cumulative percentage of the performance of machines B, G and H, I and J, F, and E are 44.99%, 56.25%, 67.51%, 78.55%, and 89.52% respectively.

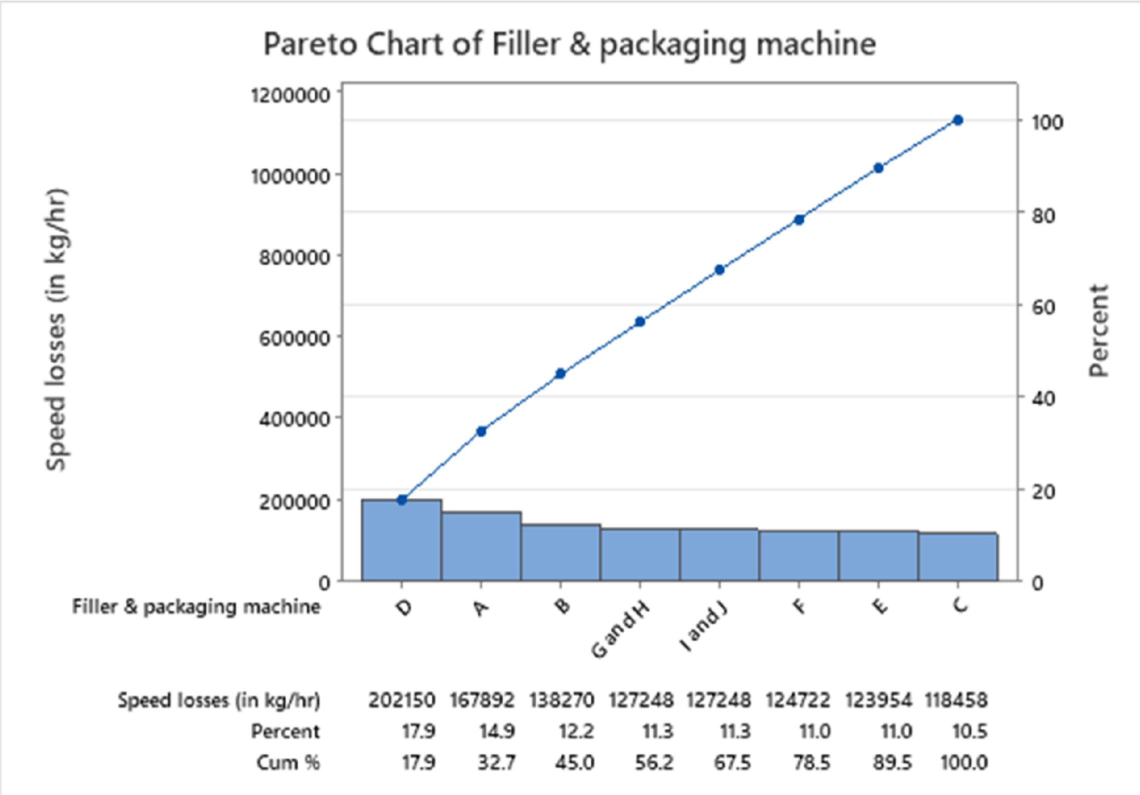


Figure 4.22 Pareto chart of filler & packaging machine performance

From this data, we can see that different machines have different levels of performance. It's no surprise that Machine D has the highest performance since it has the highest cumulative percentage among all the machines. However, it is important to note that the individual performance of a machine is not captured in the cumulative percentage performance.

Overall, this chart used to identify which machines are performing well and which ones need further improvement. It can also help in planning maintenance schedules, identifying bottlenecks, and optimizing the production process.

From the data on the different types of speed losses of the filler and packaging machines, some common speed losses may include equipment downtime, changeover time, and slow running speeds. Once we have this data, we can use a pie chart to visually represent the proportion of each type of speed loss. This is used to identify which types of losses are the most significant and prioritize improvements to increase performance.

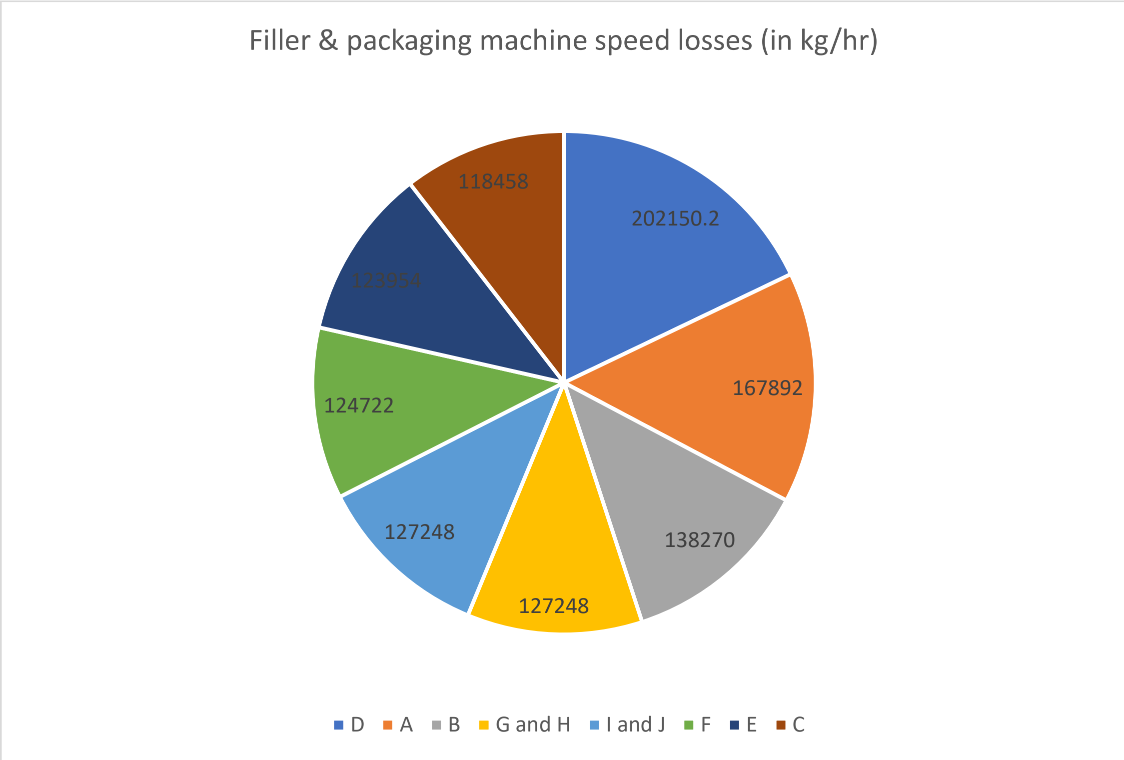


Figure 4.23 Pie chart representation of filler & packaging machine speed loss

A visually represent the distribution of speed losses among the filler and packaging machines. Each machine's speed loss value converted into a percentage of the total speed losses. The resulting chart show the proportional contribution of each machine to the overall speed losses. While Pareto chart: arranges the machines in descending order based on their speed losses.

The data over time in a run chart, potentially identify non-random variation and trends in filler and packaging machines performance. differences such as variations in total speed for a machine would stand out visually. Also compare the performance of each filler and packaging machines machine over time to assess differences in consistency. To know the pattern of the big data on auxiliary grand machine from real nonrandom behavioral big data sources on tip-track machines, we used a run chart. This chart was used to predict the future pattern by analyzing it. So, the run chart of filler and packaging machines machine pattern trends is expressed in the below chart.

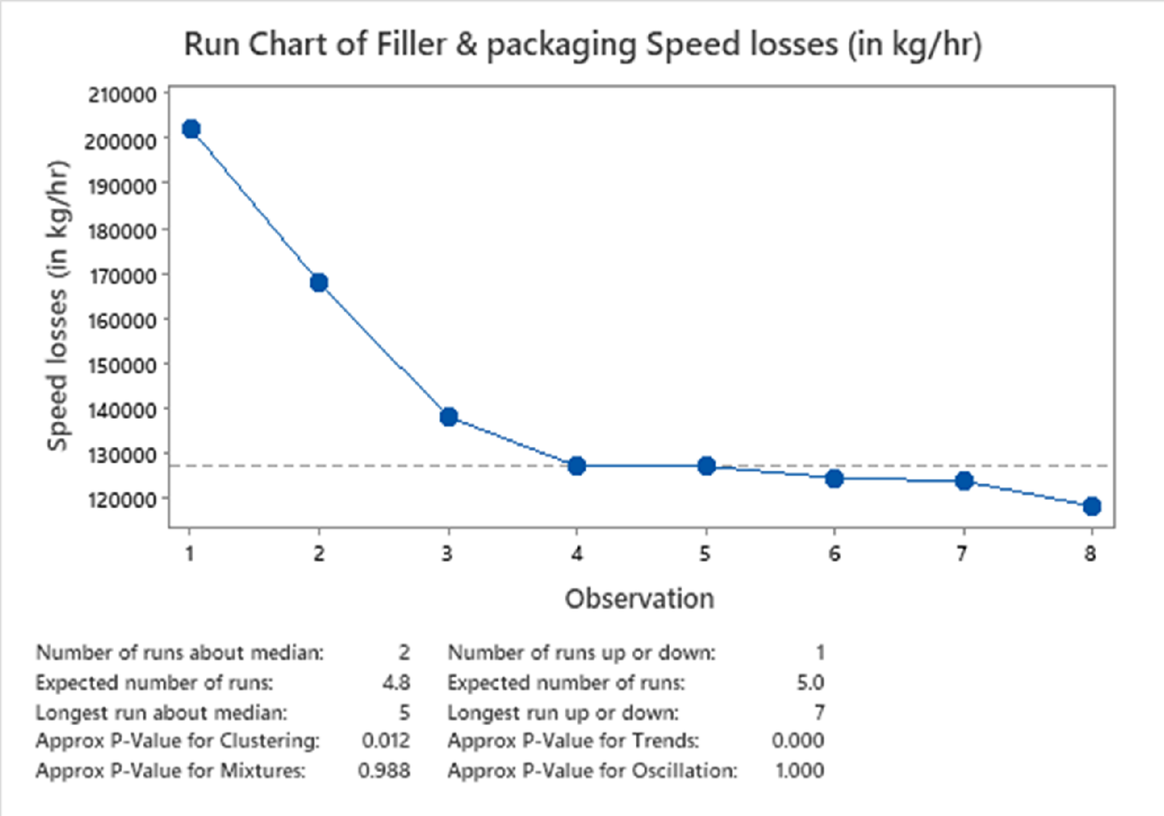


Figure 4.24 Run chart data trend of filler & packaging speed loss

All over calculation analysis of performance for auxiliary grand machine and filler & packaging machine

$$\text{Performance auxilary machine} = \frac{\text{Actual production time}}{\text{planned production time}} \ldots\ldots\ldots (from\ equ\ 2.4)$$

$$= \frac{\text{Actual speed}}{\text{Design capacity speed}}$$

$$= \frac{\frac{32886673.08\text{kg}}{\text{hr}}}{\frac{34944000\text{kg}}{\text{hr}}}$$

$$= 0.9411$$

$$= 94.11\%$$

$$\text{Performance filler \& pakaging} = \frac{\text{Actual speed}}{\text{Design capacity speed}}$$

$$= \frac{\frac{2508000\text{kg}}{\text{hr}}}{\frac{1378057.8\text{kg}}{\text{hr}}}$$

$$= 0.5495$$

$$= 54.95\%$$

4.3.3.2 Cause and effect diagram filler & packaging machine performance losses

The cause-and-effect diagram of filler and packaging machines in accordance with speed loss is similar to the cause-and-effect diagram of filler and packaging machines in accordance with downtime on figure 4.14. The only difference is that the effect of this diagram is speed loss, but in the above, it is downtime.

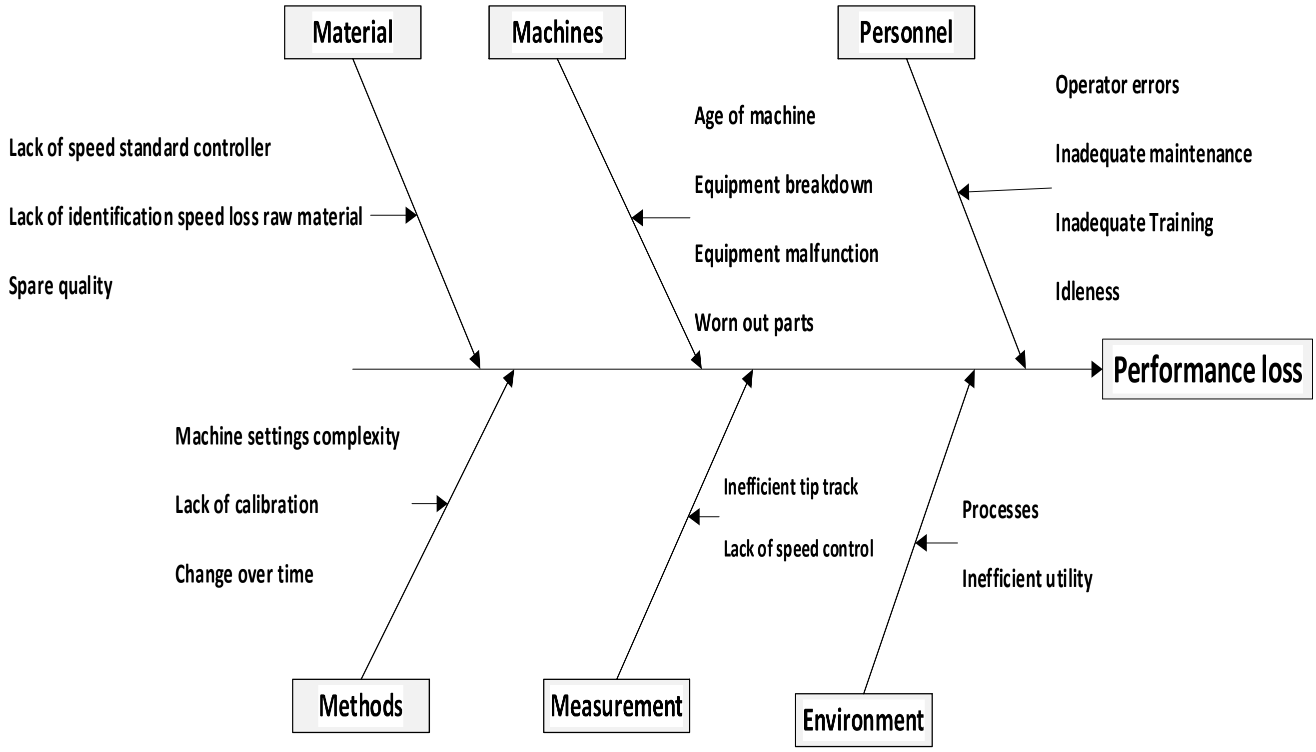


Figure 4.25 Fish bone diagram of filler and packaging machine speed loss

The above fishbone diagram of filler and packaging machine downtime in figure 4.14, the main categories to consider are the six Ms: Manpower, Machine, Material, Method, Measurement, and Mother Nature. Each of these categories can be broken down further into specific factors that can cause downtime, such as operator error, equipment failure, low-quality materials, inefficient processes, inaccurate measurements, and environmental factors like temperature or humidity.

Similarly, when creating a fishbone diagram for speed losses, the main categories to consider are again the six Ms, but with a focus on factors that can affect the speed of operation.

Once the root causes of downtime have been identified using the fishbone diagram in above figure 4.14, manufacturers can develop strategies to address these issues. This may involve implementing new training programs, upgrading equipment, improving processes, or sourcing higher-quality materials.

By understanding these factors, manufacturers can develop effective solutions to improve their overall performance and increase productivity.

Equipment downtime

|

Equipment malfunction

|

Worn out parts

|

Inadequate Maintenance

|

Lack of calibration

|

Speed Loss of Filler and Packaging Machine

|

Changeover Time

|

Inefficient Processes

|

Inadequate Training

|

Operator Error

Figure 4.26 Speed loss of filler and packaging machine in Hilina PLC

In this diagram, the problem statement is the speed loss of the filler and packaging machine in Hilina energy enriched food manufacturing industry. The main causes of the problem are divided into two categories: equipment downtime and changeover time. Under equipment downtime, we have identified three sub-causes: equipment malfunction, worn out parts, and inadequate maintenance. These are some common reasons for equipment downtime that can result in speed loss. Under changeover time, we have identified three sub-causes: inefficient processes, inadequate training, and operator error. These are some common reasons for changeover time that can cause delays and decrease overall speed. By identifying these root causes, we can develop solutions to address them and improve the speed of the filler and packaging machine in energy enriched food manufacturing industry.

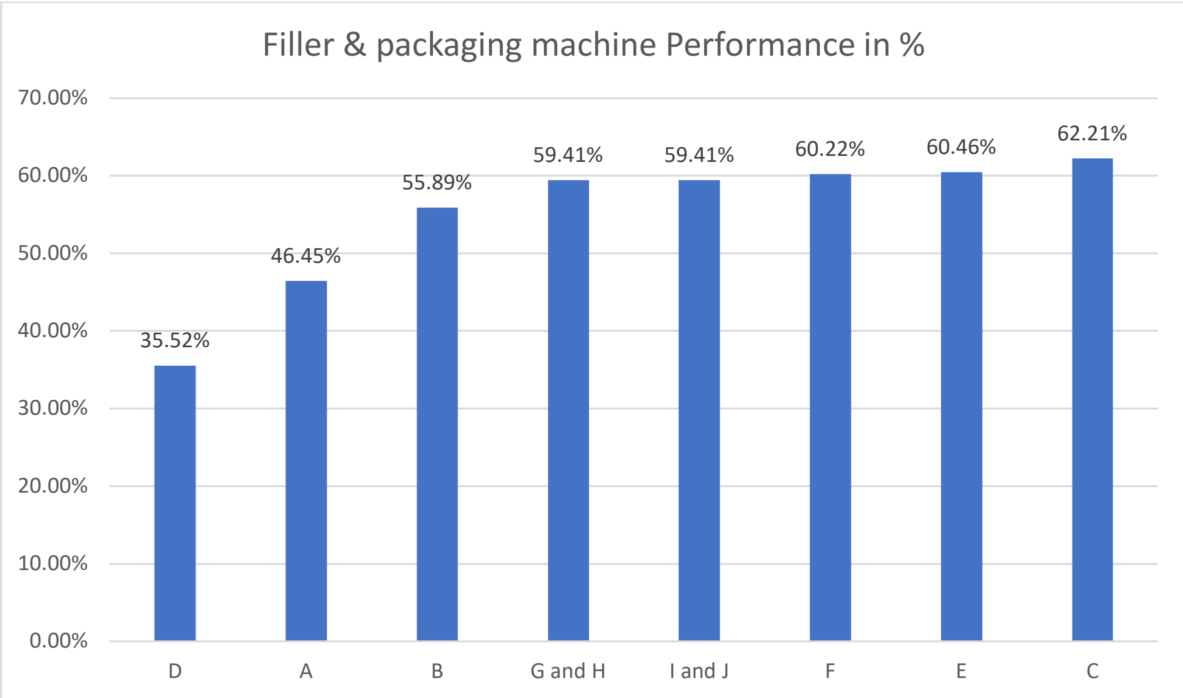


Figure 4.27 Filler & packaging performance

4.3.4 Quality losses trend analysis and findings

A manufacturing company's quality loss trend's underlying reasons are found by combining data analysis methods with quality improvement procedures. Data collection and analysis to spot patterns and trends in quality measures like defect rates, scrap rates, and customer complaints are one way to do this. To determine the root causes of quality concerns, employ root cause analysis methodologies like the five whys or Fishbone diagrams.

Once the main causes of quality losses have been identified, personalized solutions to these problems can be developed and put into practice using quality improvement approaches like Six Sigma, Total Quality Management (TQM), or lean manufacturing. These remedies include adjustments to processes, new equipment, employee training, or other initiatives geared toward lowering errors, strengthening quality control, and raising customer satisfaction.

Manufacturing industries identify areas for improvement and make data-driven decisions to maximize quality performance and reduce losses by recording quality measures over time and analyzing patterns. It is possible to identify the main reasons for quality losses and take specific steps to raise product quality and customer satisfaction by fusing data analysis tools with quality improvement methodologies.

Table 4.16 Quality loss on Auxiliary grand machines

Auxiliary grand machine	Sensitive area	Bad product	Loss in %	Total product	Good product	Reason of bad product
Roaster	Chamber	213.92	10.3	2,077.78	1,863.86	Hull, moisture, size of raw material
Sortex	Camera	92.92	4.99	1,863.86	1,770.94	Infested material, size of raw material
Pre blend	Vessel	42.43	1.06	4,002.33	3,959.90	Tune leveler, cleaning
Grinder & mixer A	Brushes	39.42	1.00	3,959.90	3,920.48	File adjustment
Blend	Vessel	92.36	1.32	6,997.36	6,905.00	Tune leveler, cleaning
Grinder & mixer B	Brushes	90.00	1.30	6,905.00	6,815.00	File adjustment
Vacuum pump	Mechanical seal	1.22	0.02	6,815.00	6,813.64	Over flow
Thermal treatment	Sensor	1.36	0.02	6,813.64	6,812.42	Power fluctuation
Total				39434.87	38861.2	
Filler & packaging	Eye mark	121.31	1.78	6,812.42	6,691.11	Leakage, seal, scale, sachet plaster, eye mark, dose

Source: which is quality of machine from technique & production department.

The data in Table 4.16 above shows the quality loss experienced on various auxiliary grand machines used in the production process. The machines listed include a roaster, Sortex, pre-blending, grinder and mixer A, blend, grinder and mixer B, vacuum pump, thermal treatment, and filler and packaging. The sensitive areas and reasons for bad products are also listed for each machine. The data provides insight into the factors that contribute to quality loss in the production process and can be used by the technique and production departments to improve the quality of the final product.

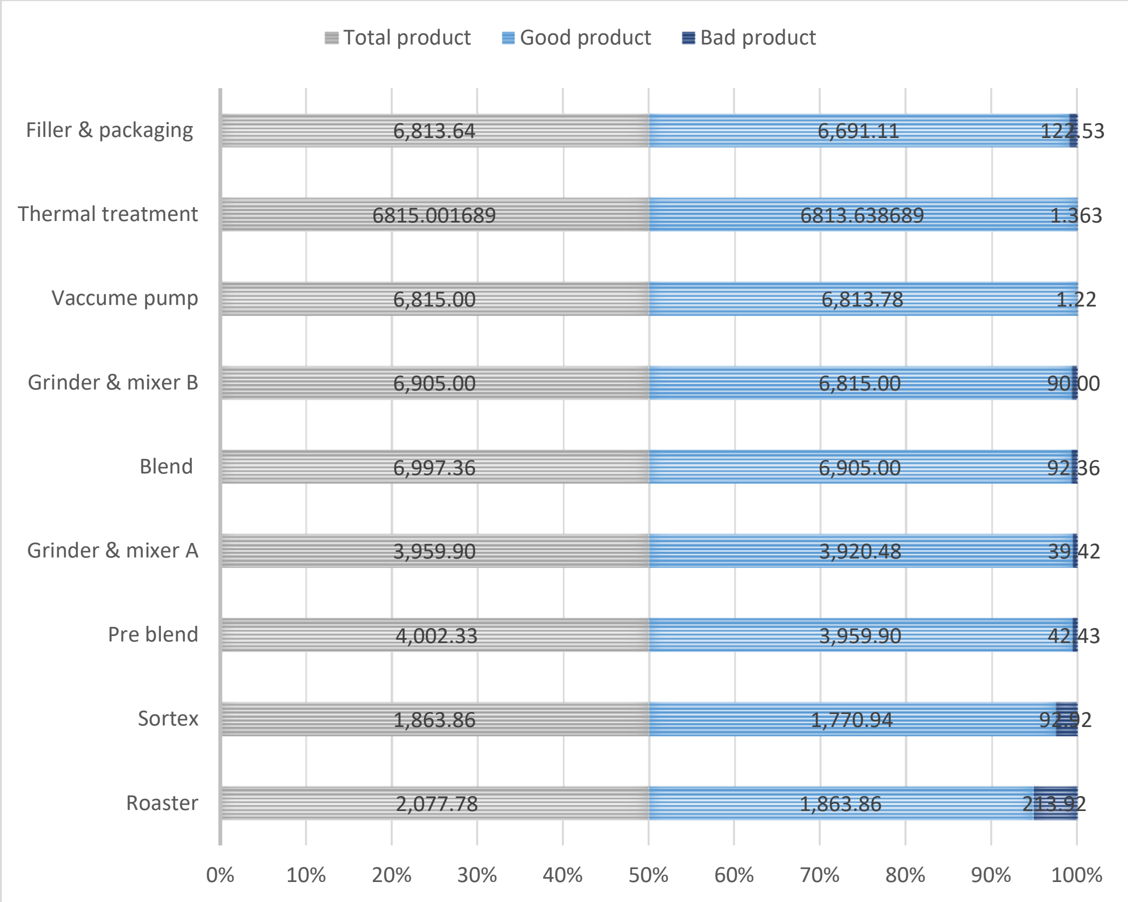


Figure 4.28 Auxiliary grand machine quality status

The basic idea for this summarized chart is to show the quality loss of different auxiliary grand machines in terms of bad product, loss percentage, and reason for bad product. The chart is based on the total product and good product of each machine. Depend on the data table in 4.16 also shows the sensitive areas of each machine that affect quality loss. The data is sourced from the technique and production departments of the company (Appendices IA and IB). The chart also used to identify the main causes of quality loss and improve the performance of the auxiliary grand machines.

The mathematical analysis of quality of auxiliary machine is

$$\text{Quality auxiliary machine i} = \frac{\text{No of good product machine i}}{\text{Total No of product machine i}} \ldots \ldots (from\ equ\ 2.7)$$

Were:

Machine i- Roaster, Sortex, Pre-blend, Grinder & Mixer A, Blend, Grinder & Mixer B, Vacuum pump, Thermal treatment and filler and packaging machine

Section I (Raw material preparing zone)

$$\text{Quality roaster machine} = \frac{\text{No of good product producing in roaster machine}}{\text{Total No of product producing in roaster machine}}$$

$$= \frac{1863.86\text{tone}}{2077.78\text{tone}}$$

$$0.8970$$

$$= 89.70\%$$

$$\text{Quality Sortex machine} = \frac{\text{No of good product producing in Sortexmachine}}{\text{Total No of product producing in Sortex machine}}$$

$$= \frac{177094\text{tone}}{1863.86\text{tone}}$$

$$0.9501$$

$$= 95.01\%$$

Section II & III (Production and sorting zone)

$$\text{Quality Pre} - \text{blend machine} = \frac{\text{No of good product producing in Pre} - \text{blend machine}}{\text{Total No of product producing in Pre} - \text{blend machine}}$$

$$= \frac{3959.90\text{tone}}{4022.33\text{tone}}$$

$$0.9894$$

$$= 98.94\%$$

$$\text{Quality Grinder \& mixer machine A} = \frac{\text{No of good product producing in Grinder \& mixer A}}{\text{Total No of product producing in Grinder \& mixer A}}$$

$$= \frac{3920.48\text{tone}}{3959.90\text{tone}}$$

$$0.9868$$

$$= 99.00\%$$

$$\text{Quality Blend machine} = \frac{\text{No of good product producing in Blend machine}}{\text{Total No of product producing in Blend machine}}$$

$$= \frac{6905\text{tone}}{6997.36\text{tone}}$$

$$0.9868$$

$$= 98.68\%$$

$$\text{Quality Grinder \& mixer machine B} = \frac{\text{No of good product producing in Grinder \& mixer B}}{\text{Total No of product producing in Grinder \& mixer B}}$$

$$= \frac{6815\text{tone}}{6905\text{tone}}$$

$$0.9870$$

$$= 98.70\%$$

$$\text{Quality Vacuum machine} = \frac{\text{No of good product producing in Vacuum machine}}{\text{Total No of product producing in Vacuum machine}}$$

$$= \frac{6813.64\text{tone}}{6815\text{tone}}$$

$$0.9998$$

$$= 99.980\%$$

$$\text{Quality Thermal treatment machine}$$

$$= \frac{\text{No of good product producing in Thermal machine}}{\text{Total No of product producing in Thermal machine}}$$

$$= \frac{6812.42\text{tone}}{6815\text{tone}}$$

$$0.9998$$

$$= 99.982\%$$

$$\text{Quality filler \& packaging machine} = \frac{\text{No of good product producing in filler \& packaging}}{\text{Total No of product producing in filler \& packaging}}$$

$$= \frac{6691.11\text{tone}}{6812\text{tone}}$$

$$= 0.9823$$

$$= 98.23\%$$

After the mathematical analysis of the quality of the auxiliary machine, a Pareto analysis is necessary to determine the priority for enhancing the quality of each machine. The Pareto analysis is used to identify the machines that contribute the most to quality loss and therefore require the most attention.

Once the priority machines have been identified, a cause-and-effect diagram is used to investigate the major influences on quality loss. This was used to identify the root causes of quality loss and provide insight into how to improve the quality of the production process. By using both mathematical and qualitative analysis, the production team can develop a comprehensive plan to improve the quality of the final product.

Table 4.17 Pareto table of auxiliary grand machine quality

Equipment	Quality loss (in tone)	Cumulative	Percentage	Cumulative percentage
Roaster	213.92	213.92	30.78%	30.78%
Filler & packaging	121.31	335.22	17.46%	48.24%
Sortex	92.92	428.14	13.37%	61.61%
Blend	92.36	520.50	13.29%	74.90%
Grinder & mixer B	90.00	610.50	12.95%	87.85%
Pre blend	42.43	652.94	6.11%	93.95%
Grinder & mixer A	39.42	692.36	5.67%	99.63%
Thermal treatment	1.36	693.72	0.20%	99.82%
Vacuum pump	1.22	694.95	0.18%	100.00%

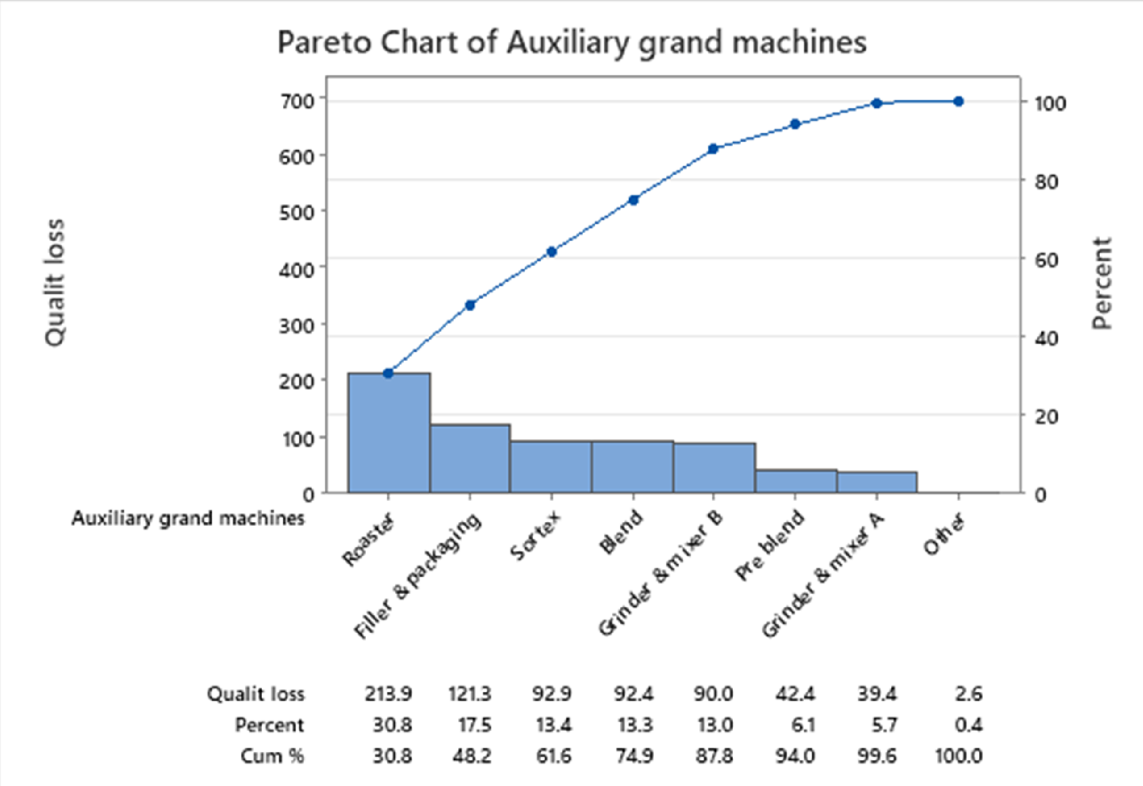


Figure 4.29 Pareto chart of auxiliary grand machine quality

From this Pareto chart is to show the quality loss of auxiliary grand machine in terms of cumulative percentage. The chart that displays data in descending order of importance or frequency. The chart is based on the principle that a few factors usually account for the majority of the impact or occurrences.

In the given above table 4.17, the auxiliary grand machine is listed along with the corresponding quality loss in terms of tone. The cumulative quality loss and cumulative percentage are also mentioned. The Pareto chart is based on the cumulative percentage of the quality loss for each auxiliary grand machine.

The chart clearly shows that a majority of the quality losses are caused by the Roaster, Filler & Packaging, and Sortex machine. These three auxiliary grand machines alone account for more than 60% of the total quality loss. Therefore, improving the quality of these auxiliary grand machine should be given high priority in order to have a significant impact on the overall quality of the product. The chart also identifies the factors that have the most impact on a system or process, and it prioritizes the areas of improvement that will have the greatest effect. By analysing the chart, we can identify the areas that require improvement and take corrective measures to improve the overall quality of the product.

These quality distributions of auxiliary grand machines are clearly visualized in the below pie chart, Figure 4.30. By interpreting the data using a pie chart, we can quickly identify which machines are having the greatest impact on the overall quality of the factory's products. This can help us narrow down the issues and focus our efforts on addressing the biggest culprits. We can also use the chart to track our progress over time and see if our interventions are having the desired impact on improving machine quality.

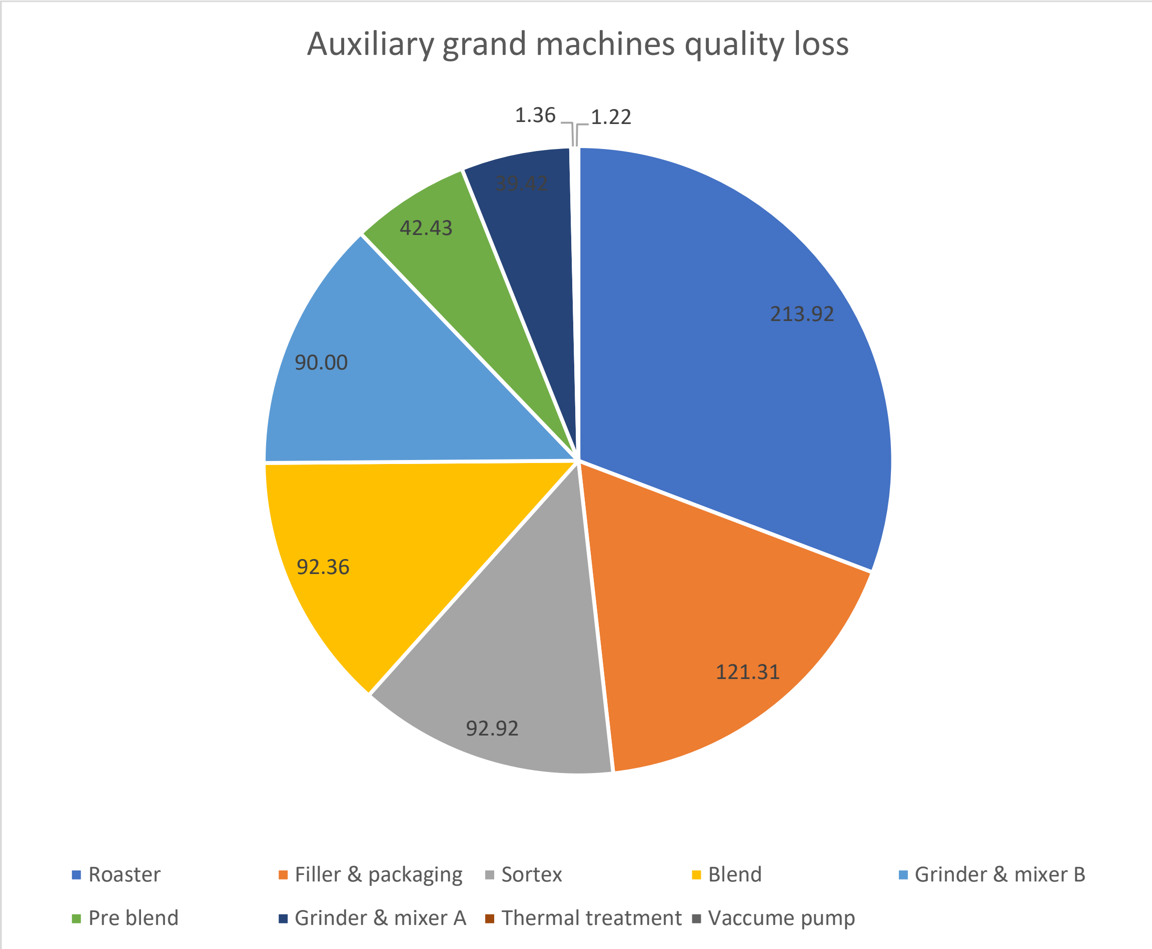


Figure 4.30 Pie chart of auxiliary grand machine quality

Figure 4.30. The pie chart shows the percentage of quality loss for each machine in terms of a slice of the pie. The pie chart can help to identify the machines that have the highest quality loss and to prioritize the improvement actions. The chart also helps to monitor the changes in quality over time and to evaluate the effectiveness of the improvement actions and a simple and intuitive way to display data and to compare different categories or factors.

In summary, from the mathematical analysis of the quality of the auxiliary grand machine and its Pareto analysis in the above tables 4.16, 4.17, and figure 4.29, interpret the result for the following cluster chart of the auxiliary grand machine quality percentage.

The mathematical analysis and Pareto analysis of the quality of the auxiliary grand machine and introduces the cluster chart of the auxiliary grand machine quality percentage. The chart shows the quality percentage of each auxiliary grand machine in terms of good product and bad product. This helps to compare the quality of auxiliary grand machines, identify areas for improvement, show the variation in quality across different auxiliary grand machines, and highlight outliers or exceptions.

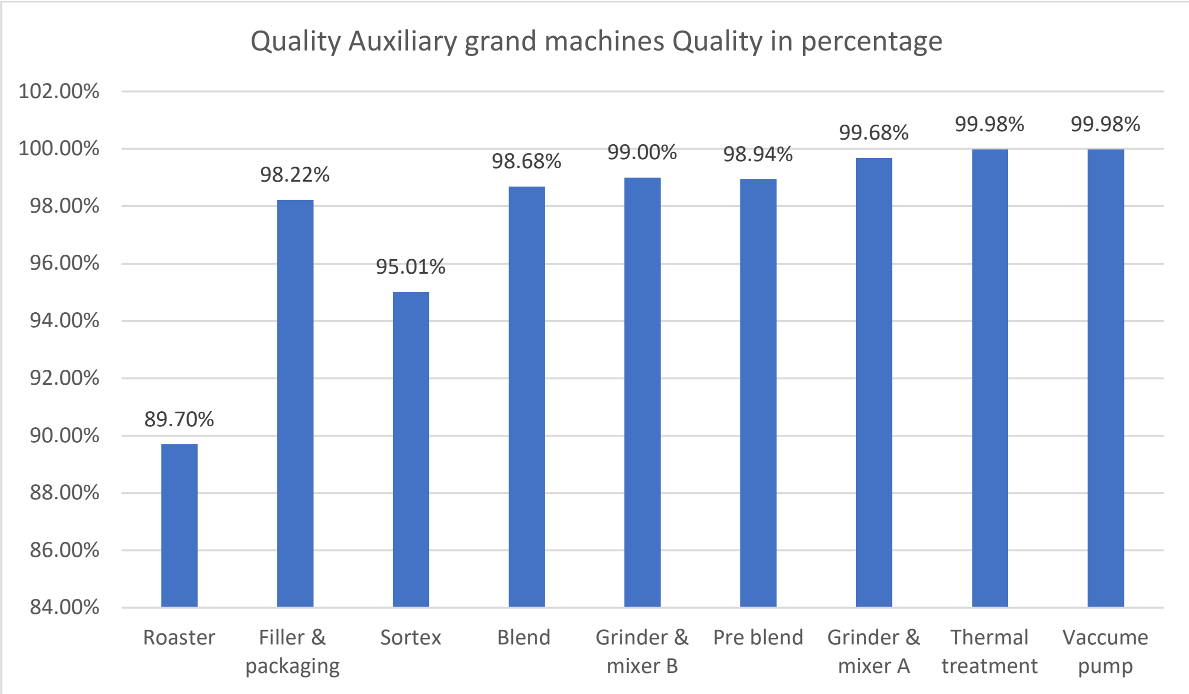


Figure 4.31 Auxiliary grand machine quality chart

From chart displaying data and for making comparisons and contrasts between each auxiliary grand machine's peak quality (99.68% of Grinder and Mixer machine A, thermal machine, and vacuum pump machine 99.98%, and the lowest quality performance machine of Roaster and Sortex machine), and the other remaining intermediate auxiliary grand machines. From discussion further investigation analysis required to enhance the reason of decline their quality of auxiliary grand machine.

Table 4.18 Quality of output on Sachet, Plumpy sup and nut products

Output	Feature	Total product produce or used	Good product produce or used	Loss product	Quality	Quality
Sachet	Nut in meter	7169636.817	7154301.66	15335.16	99.79%	99.78%
	Sup in meter	3155296.492	3147997.50	7298.99	99.77%	
Plumpy	Nut in tone	4757.55595	4747.38	10.18	99.79%	99.78%
	Sup in tone	1948.23676	1943.73	4.51	99.77%	

Source production department, logbook, tip-track from January to December 2022 (Appendix IA

4.3.3.1 Cause and effect diagram auxiliary grand machine quality losses

The common quality loss of selected machines used in raw material preparation, such as roaster, Sortex, filler and packaging, blend, and pre-blend machines. It highlights that the quality loss in these machines is due to the raw material (peanut) neatness and labour skill, especially on roasters and Sortex machines. The local and imported peanut with better neatness is preferred over local peanut due to issues like moisture, hull, infestation, and non-uniform size of peanuts mentioned in table 4.2. It then goes on to say that all points are against availability and performance on the filler and packaging, blend, pre-blend, grinder & mixer AB, vacuum pump, and thermal machines, which affects their quality.

In addition to the cause-and-effect diagram that was previously mentioned regarding availability and performance losses in figures 4.7 and 4.20, it is important to thoroughly analyse and understand all potential sources of quality loss in order to improve overall performance and efficiency.

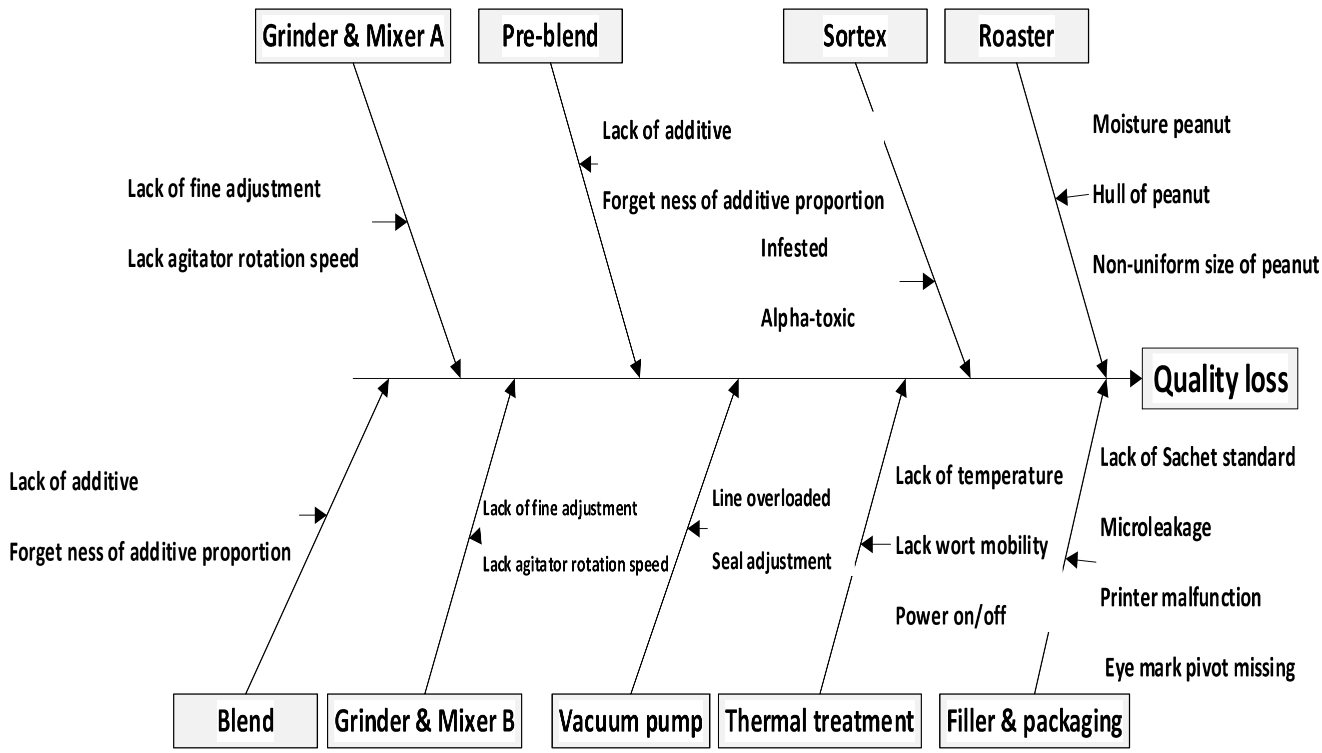


Figure 4.32 Fishbone diagram of auxiliary grand machine quality loss

The basic idea conveyed in the above fishbone diagram is that the quality loss of these auxiliary machines used in raw material preparation is primarily dependent on the raw material neatness and labour skill. It emphasizes the importance of using quality raw materials that are free from issues like moisture, infestation, and non-uniform size to improve the overall quality of the end product. It also highlights the availability and performance issues on the filler and packaging, blend, and pre-blend machines, which can further impact the final product's quality.

4.4 Overall effectiveness analysis trend of auxiliary machine, filler and packaging machine

In a manufacturing organization, overall equipment effectiveness serves as a measurement and improvement indicator. These two key goals are essential in demonstrating the level of performance and the elements that have the most impact on the company.

The goal of measuring and analyzing the OEE of each piece of equipment is to reach milestones and make progress toward understanding the OEE of the overall system. According to (Feng Liua, 2018),OEE is a well-known measurement technique that can accurately reflect the state of the equipment at the production site. It is frequently used in the manufacturing sector to assess the effectiveness of the equipment and determine the best course of action for improvement.

The equipment is categorized in order to analyze the OEE of the Hilina Enriched Food manufacturing industry. The overall summary of OEE trend on Hilina enriched food organization in below table.

Auxiliary machine

Table 4.19 Auxiliary machine OEE

Auxiliary machine	Availability (in%)	Performance (in%)	Quality (in%)	OEE (in %)
Roaster machine	86.91	95.93	89.70	74.79
Sortex machine	87.41	95.71	95.01	79.49
Pre-Blend machine	86.79	93.62	98.94	80.39
Grinder & Mixer A	86.08	91.67	99.00	78.12
Blend machine	86.10	93.94	98.68	79.81
Grinder & Mixer B	85.75	91.39	98.70	77.35
Vacuum pump	87.42	94.92	99.98	82.96
Thermal treatment	87.88	95.72	99.98	84.10
OEE	86.79	94.11	97.50	79.64

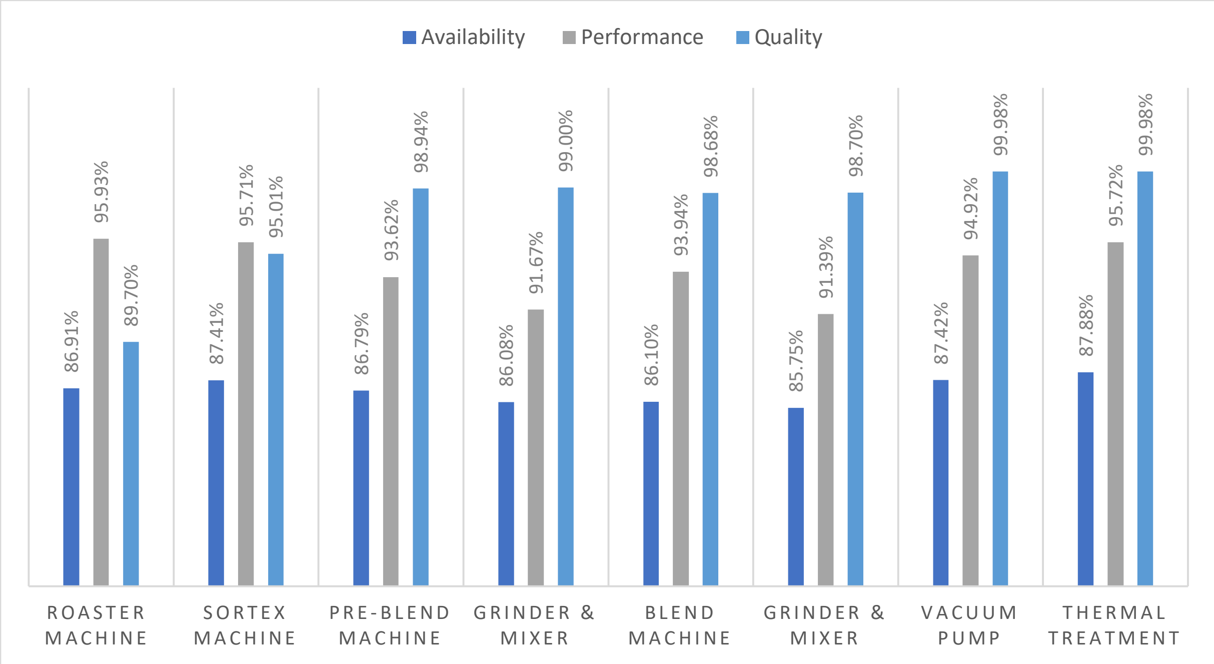


Figure 4.33 Auxiliary machine OEE

To calculate the overall OEE of the factory, we need to combine the Availability, Performance, and Quality percentages for all the machines and then calculate the weighted average OEE.

First, we need to calculate the weighted average of the Availability, Performance, and Quality percentages for all machines. To do this, we multiply each percentage by the weight of the corresponding machine (i.e., the proportion of time it takes in the overall process). Then, we sum up these products across all machines.

To calculate the Auxiliary machine weighted average of the Availability, Performance, Quality percentages and OEE, we use the following formula:

$$\text{Weighted Availability} = \frac{(A1 * W1) + (A2 * W2) + \ldots + (An * Wn)}{\text{Total weight}} \ldots\ldots\ldots\text{(from equ 2.10)}$$

$$\text{Weighted Performance} = \frac{(P1 * W1) + (P2 * W2) + \ldots + (Pn * Wn)}{\text{Total weight}} \ldots\text{(from equ 2.11)}$$

$$\text{Weighted Quality} = \frac{(Q1 * W1) + (Q2 * W2) + \ldots + (Qn * Wn)}{\text{Total weight}} \ldots\ldots\ldots\text{(from equ 2.12)}$$

$$\text{OEE} = \text{weighted averages of the Availability} * \text{weighted averages Performance} \\ * \text{weighted averages Quality} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \text{(from equ 2.13)}$$

Were

A1, A2, ..., A8 are the Availability percentages for each machine,

P1, P2, …., P8 are Performance percentages for each machine

Q1, Q2, …., Q8 are Quality percentages for each machine

W1, W2, ..., W8 are their weights.

The calculation of the OEE involves weighting each of these factors according to their relative importance and then multiplying them together to obtain a single score. A higher score indicates greater efficiency and effectiveness, while a lower score indicates room for improvement (from an interview with experts).

The wight is depended on to do operations in total coverage out of 100 in the factory; the Hilina enriched food manufacturing company gives these wights on its distribution, i.e., the auxiliary machine is 50% wight, the filler and packaging machine is 13% wight, and the product in and out is 37% wight cover including utility.

The pre-blend and blend machines are equal in weight, which is W3, W5, which is equal to 10 (ten) in weight because these machines do additional tasks that add additives to their processes, but the remaining machines, Sortex, Grinder and mixer A B, vacuum pump, and thermal machine, which are W1, W2, W4, W6, W7, and W8, are equal to 5 (five) in weight.

Using the data in the given table, we can calculate the weighted averages for Availability, Performance, and Quality as follows:

$$\text{Weighted Availability}$$

$$= \frac{\begin{pmatrix} (86.91\% * 5) + (87.41\% * 5) + (86.79\% * 10) + (86.08\% * 5) + + \\ (86.10\% * 10) + (85.75\% * 5) + (87.42\% * 5) + (87.88\% * 5) \end{pmatrix}}{50}$$

$$= 86.79\%$$

$$\text{Weighted Performance}$$

$$= \left(\frac{\begin{gathered}(95.93\% * 5) + (95.71\% * 5) + (93.62\% * 10) + (91.67\% * 5) + \\ (93.94\% * 10) + (91.39\% * 5) + (94.92\% * 5) + (95.72\% * 5)\end{gathered}}{50} \right)$$

$$= 94.11\%$$

$$\text{Weighted Quality}$$

$$= \frac{\begin{pmatrix}(89.70\% * 5) + (95.01\% * 5) + (98.94\% * 10) + (99.00\% * 5) + \\ (98.68\% * 10) + (98.70\% * 5) + (99.98\% * 5) + (99.98\% * 5)\end{pmatrix}}{50}$$

$$= 97.50\%$$

Now, we can calculate the overall OEE by multiplying the weighted averages of the Availability, Performance, and Quality

$$\textbf{OEE auxilary machine}$$

$$\begin{gathered} = \textbf{weighted averages of the Availability} * \textbf{weighted averages Performance} \\ * \textbf{weighted averages Quality} = \mathbf{A} * \mathbf{P} * \mathbf{Q} \ldots\ldots(\textbf{from equ } \mathbf{2.13}) \end{gathered}$$

$$= \mathbf{86.79}\% * \mathbf{94.11}\% * \mathbf{97.50}\%$$

$$= \mathbf{79.64}\%$$

Based on this analysis, it can be concluded that the OEE (Overall Equipment Effectiveness) of the auxiliary machines in the Hilina Enriched Energy Manufacturing Industry is generally quite high, with most machines showing OEE values in the range of 74.79% to 84.10%.

However, it is important to note that there is still room for improvement, especially in terms of the performance percentages of some of the machines. For instance, the Grinder and Mixer A and B machines have performance percentages of 91.67% and 91.39%, respectively, which are relatively lower than the other machines. Improving the performance percentages of the machines can help to further increase the overall OEE of the manufacturing industry.

In addition, while the quality percentages of all machines are generally high, the roaster machine's quality percentage is relatively lower than other machines. Therefore, it is important for the manufacturing industry to pay attention to improving the quality of the roaster machine.

Overall, the Hilina Enriched Energy Manufacturing Industry seems to be performing well in terms of OEE for the auxiliary machines, but continuous improvement is necessary to sustain and increase this performance.

Filler and packaging machine

Table 4.20 Filler & packaging machine OEE

Filler & packaging	Availability (in %)	Performance (in %)	Quality (in%)	OEE (in %)
A	41.08	46.45	90.10	17.19
B	64.94	55.89	89.38	32.44
C	75.17	62.21	83.98	39.27
D	67.54	35.52	90.53	21.72
E	70.18	60.46	87.98	37.33
F	57.23	60.22	86.53	29.82
G	69.17	59.41	96.27	39.56
H	69.17	59.41	82.68	33.98
I	72.83	59.41	96.27	41.65
J	72.83	59.41	96.27	41.65
OEE	66.60	55.83	90.00	33.46

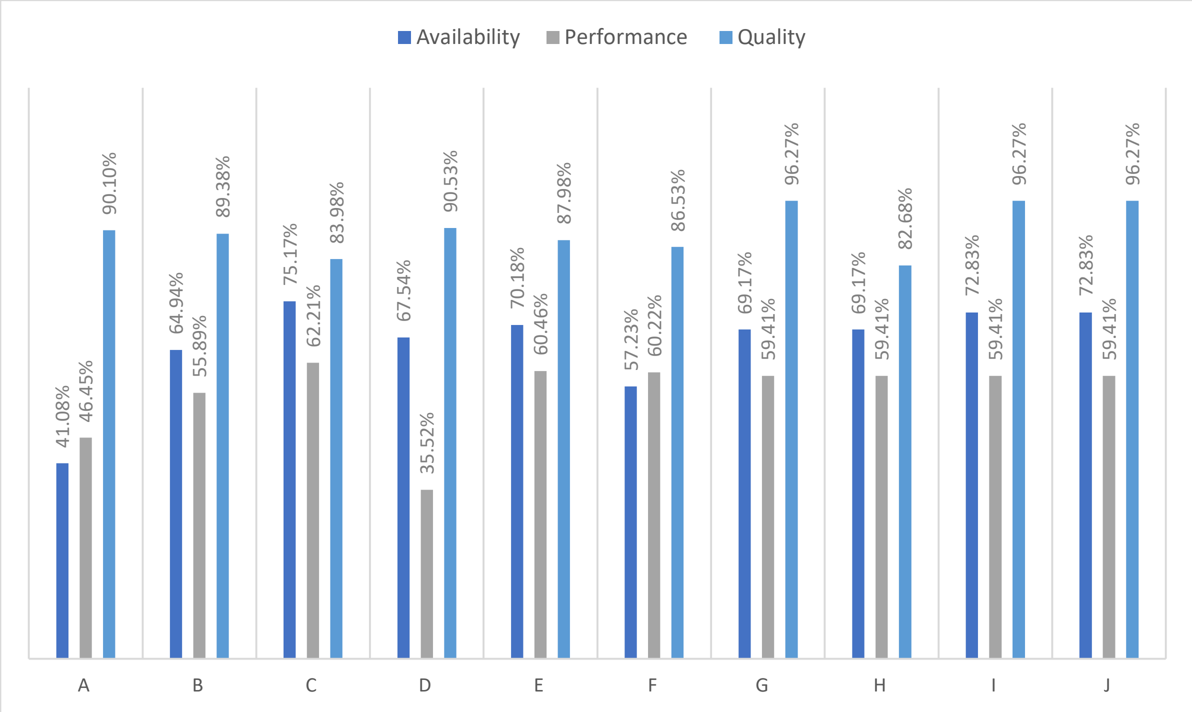


Figure 4.34 OEE trend of auxiliary, filler & packaging machine respectively

To calculate the overall OEE for the filler & packaging machines, we need to calculate the weighted average of the Availability, Performance, and Quality percentages for all the ten machines.

To calculate the filler and packaging machine weighted average of the Availability, Performance, Quality percentages and OEE, we use the following formula:

$$\text{Weighted Availability} = \frac{(\text{A1} * \text{W1}) + (\text{A2} * \text{W2}) + \ldots + (\text{An} * \text{Wn})}{\text{Total weight}} \ldots \ldots (\text{from equ } 2.10)$$

$$\text{Weighted Performance} = \frac{(\text{P1} * \text{W1}) + (\text{P2} * \text{W2}) + \ldots + (\text{Pn} * \text{Wn})}{\text{Total weight}} \ldots . (\text{from equ } 2.11)$$

$$\text{Weighted Quality} = \frac{(\text{Q1} * \text{W1}) + (\text{Q2} * \text{W2}) + \ldots + (\text{Qn} * \text{Wn})}{\text{Total weight}} \ldots \ldots \ldots . (\text{from equ } 2.12)$$

$$\text{OEE auxilary machine} = \text{weighted averages of the Availability} * \text{weighted averages Performance} * \text{weighted averages Quality} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. \text{(from equ 2.13)}$$

Were

A1, A2, ..., A10 are the Availability percentages for each machine,

P1, P2, …., P10 are Performance percentages for each machine

Q1, Q2, …., Q10 are Quality percentages for each machine

W1, W2, ..., W10 are their weights.

The filler and packaging machine is dependent on its status. The C and E filler machines are equal in weight, which is W3, W5, which is equal to 2 (two) in weight because these machines are effective in their processes, but the remaining machines, A, B, D, F, G, H, I, and J filler machines, which are W1, W2, W4, W6, W7, W8, W9, and W10, are equal to 1 (one) in weight since the machines obviously host external downtime issues, which is a break for a reason.

$$\text{Weighted Availability} = \frac{\begin{pmatrix}(41.08 \text{ x } 1) + (64.94 \text{ x } 1) + (75.17 \text{ x } 2) + (67.54 \text{ x } 1) + (70.18 \text{ x } 2) + (57.23 \text{ x } 1) + \\ (69.17 \text{ x } 1) + (69.17 \text{ x } 1) + (72.83 \text{ x } 1) + (72.83 \text{ x } 1)\end{pmatrix}}{13} = 66.60\%$$

$$\text{Weighted Performance} = \frac{\begin{pmatrix}(46.45 \text{ x } 1) + (55.89 \text{ x } 1) + (62.21 \text{ x } 2) + (35.52 \text{ x } 1) + (60.46 \text{ x } 2) + (60.22 \text{ x } 1) + \\ (59.41 \text{ x } 1) + (59.41 \text{ x } 1) + (59.41 \text{ x } 1) + (59.41 \text{ x } 1)\end{pmatrix}}{13} = 55.83\%$$

$$\text{Weighted Quality} = \frac{\begin{pmatrix}(90.10 \text{ x } 1) + (89.38 \text{ x } 1) + (83.98 \text{ x } 2) + (90.53 \text{ x } 1) + (87.98 \text{ x } 2) + (86.53 \text{ x } 1) + \\ (96.27 \text{ x } 1) + (82.68 \text{ x } 1) + (96.27 \text{ x } 1) + (96.27 \text{ x } 1)\end{pmatrix}}{13} = 90.00\%$$

By substituting the weighted averages of Availability, Performance, and Quality back into the formula for OEE, we can calculate the overall OEE for the filler & packaging machines:

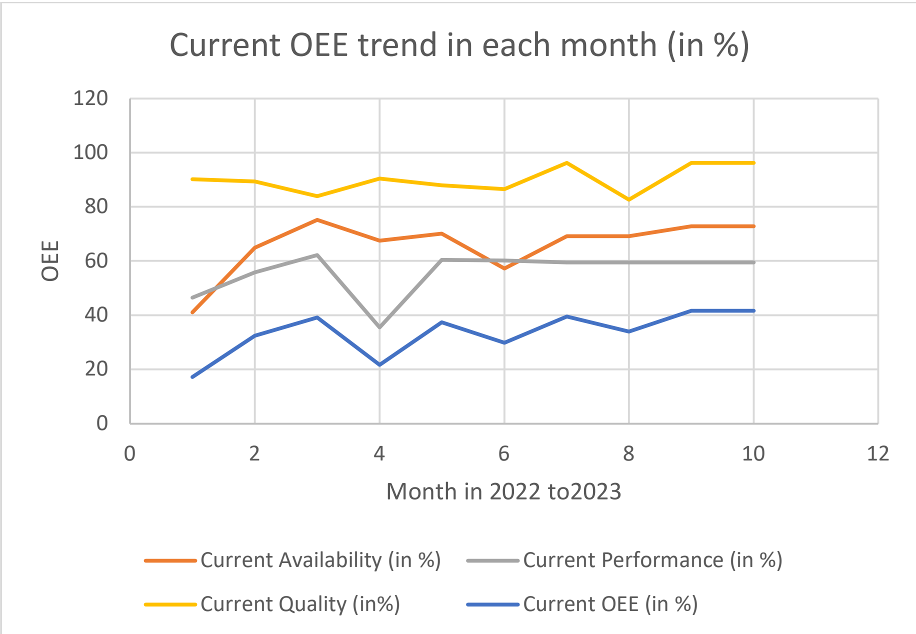
Now, we can calculate the overall OEE by multiplying the weighted averages of the Availability, Performance, and Quality

$$\textbf{OEE filler } \& \textbf{ packaging}$$

$$= \textbf{weighted averages of the Availability} * \textbf{weighted averages Performance} * \textbf{weighted averages Quality} = \mathbf{A} * \mathbf{P} * \mathbf{Q} \ldots \ldots. (\textbf{from equ 2.13})$$

$$= \mathbf{66.60\%} * \mathbf{5\ \ 583\%} * \mathbf{90.0\ \ 0\%}$$

$$= \mathbf{33.46\%}$$



Based on the data provided, it seems like the Hilina Enriched Food Manufacturing Industry has room for improvement in terms of overall equipment effectiveness (OEE) for the filler and packaging machine category, as the OEE of the overall machines is only 33.46%.

Upon further analysis, it can be seen that the performance of the machines is particularly low, with several machines showing percentages below 60%, which can significantly contribute to a low OEE. Therefore, the manufacturing industry needs to investigate the root causes of the low performance and take the necessary steps to address them in order to improve the OEE as a whole. It is also noteworthy that some machines have a relatively lower quality percentage, which affects the overall OEE of the machines. Improving the quality percentage of the machines can further help enhance the equipment effectiveness of the factory.

Overall, while the Hilina-enriched food manufacturing industry's performances have been quite good for auxiliary machines, the manufacturing industry itself should focus on enhancing the overall effectiveness of the filler and packaging machines by improving performance and quality percentages.

Therefore, the overall effectiveness of Hilina manufacturing industry we can calculate

$$\textbf{OEE Hilina manufacturing factory} = \textbf{OEE}$$

$$= \textbf{weighted averages of the Availability} * \textbf{weighted averages Performance} * \textbf{weighted averages Quality} \ldots\ldots\ldots\ldots\ldots (\textbf{from 2.13})$$

Were

Weighted averages of the Availability= {(Weighted averages of the Availability auxiliary machine*50 + Weighted averages of the Availability of filler and packaging machine*13)} / 63………., (from 2.10)

$$= \frac{\{(86.79\% * 50) + (66.60\% * 13)\}}{63}$$

$$= 82.62\%$$

Weighted averages of the Performance= {(Weighted averages of the Performance auxiliary machine*50 + Weighted averages of the Performance of filler and packaging machine*13)} / 63………., (from 2.11)

$$= \frac{\{(94.11\% * 50) + (55.83\% * 13)\}}{63}$$

$$= 86.21\%$$

Weighted averages of the Quality= {(Weighted averages of the Quality auxiliary machine*50 + Weighted averages of the Quality of filler and packaging machine*13)} / 63 …………., (from 2.12)

$$= \frac{\{(97.50\% * 50) + 90.00 * 13)\}}{63}$$

$$= 95.95\%$$

$$\mathbf{OEE} = \mathbf{weighted\ averages\ of\ the\ Availability} * \mathbf{weighted\ averages\ Performance} * \mathbf{weighted\ averages\ Quality} \dots\dots\dots\dots\dots (\mathbf{from\ 2.13})$$

$$= \mathbf{82.62}\% * \mathbf{86.21}\% * \mathbf{95.95}\%$$

$$= \mathbf{68.34}\%$$

Table 4.21 Overall current result of the auxiliary grand machine

Auxiliary machine	Availability (in%)	Performance (in%)	Quality (in%)	OEE (in %)
Auxiliary machine average weight of	86.79%	94.11%	95.50%	79.64%
Filler and packaging machine average weight	66.60%	55.83%	90.00%	33.46%
Auxiliary grand machine Average weight of	82.62%	86.21%	95.95%	68.34%
OEE of the factory		68.34%		

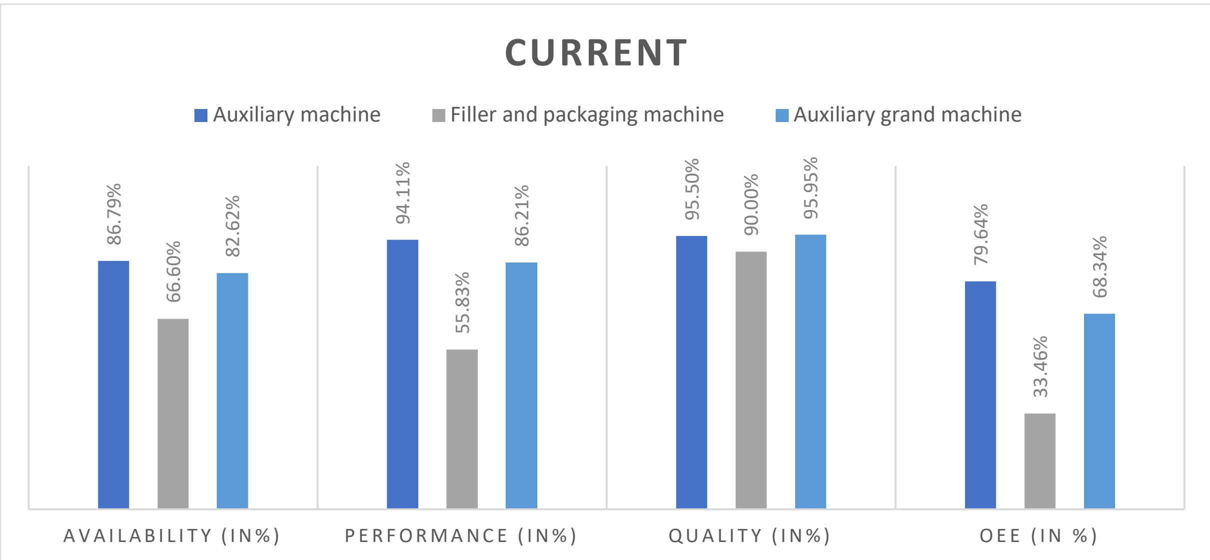


Figure 4.35 Overall current result of the auxiliary grand machine

Overall, for this analysis, the OEE for Hilina's manufacturing factory is 68.34%, which means that the factory is using 68.34% of its manufacturing time effectively. This is a low score compared to the ideal OEE of world-class, which indicates that there are many losses and inefficiencies in the manufacturing process. The analysis also shows that the auxiliary machines have a higher OEE than the filler and packaging machines, which means that the latter machines need more improvement in terms of availability, performance, and quality.

4.5 Observed problem for equipment effectiveness losses in the Hilina manufacturing industry

The OEE of the auxiliary machines in the Hilina Enriched Energy Manufacturing Industry is generally high, with most machines showing OEE values in the range of 74.79% to 84.10%. However, the availability and performance of the filler and packaging machines is particularly low, with several machines showing percentages below 60%. Additionally, some machines have a lower quality percentage, which affects the overall OEE. Due to this, the OEE for Hilina's manufacturing factory is 68.34%, which is a low score compared to standards. This implies that there is a need to enhance the factory OEE.

To enhance the factory OEE identify the root cause or reason for these OEE losses is the first stage in this study, these reasons are put in bellow table 4.22.

Table 4.22 The most common reason for OEE loss on filler and packaging machines

No. of recursion of such problems in filler and packaging machines from January to May 2023								
Machine	A	B	C	D	E	F	G & H	I & J
Dose	1	52	11	56	20	37	0	0
Three-way valve	1	6	1	1	1	1	5	1
Horizontal leakage	24	37	49	54	45	29	10	4
Vertical leakage	5	62	80	60	35	31	4	10
Nitrogen	1	5	5	4	4	2	3	5
Printer	1	43	32	36	13	36	7	16
Eye mark	1	20	28	16	15	13	13	20
Knife	2	6	9	8	9	10	48	18
Alignment	1	1	0	3	1	0	26	12

Sachet unwinding	0	1	4	4	2	3	8	2
Clutch	3	11	8	12	3	3	0	0
sealing temperature	0	0	3	1	4	0	0	0
Kentrol	1	3	1	2	1	8	1	0
Sachet congregates	0	7	0	0	0	1	0	0
Total	41	254	231	257	153	174	125	88

Source: technique department, data room (sensor, IoT), and logbooks (Appendices I–E)

This big data can be used to predict when a machine is likely to fail, allowing for preventive maintenance to be scheduled before a breakdown, speed loss, or quality loss occurs. This approach can address the issue of clutch leakage and any leakage from motors by detecting and resolving them before they cause major problems. Industry 4.0 technologies such as IoT and big data analytics can be used to monitor the health of the equipment in real-time. By leveraging sensors and other IoT devices, data about equipment performance and status can be collected and analysed continuously.

Downtime is most obviously directly interlinked with availability, but it also affects the performance and quality of auxiliary machines, fillers, and packaging machines since, due to downtime, many other problems occur, which is one of the reasons for creating defective products because if the product is not treated with a sufficient amount of treatment, it is directly converted into scrap.

The next discusses how downtime can affect the performance and quality of auxiliary machines, filler and packaging machines in a production process and its equipment's. This is due to the fact that when machines experience downtime, thermal machines lose their heat, the filler machine missing the program, leading to lower quality. This can result in the creation of defective products. The table 4.23 given below shows the amount of downtime resulting from these issues.

Table 4.23 The most common reason for OEE loss is its downtime on filler and packaging machines.

The recursion problems and other problems caused downtime (in minutes) on filler and packaging machines from January to May 2023 (151 days = 3624 hr. = 217,440 min.).								
Machine	A	B	C	D	E	F	G & H	I & J
Cleaning	945	3210	3685	3130	3120	2545	3176	2567

Planned maintenance	41280	200	165	60	0	0	0	0
Planned shutdown	0	0	0	0	1459	78	0	0
Dose	35	17912	2900	12801	4176	11429	0	0
Horizontal leakage	4013	942	1320	820	1879	1284	110	62
Vertical leakage	494	2700	2258	1408	1209	1264	59	130
Horizontal seal	1444	54	655	20	0	70	110	0
Vertical seal	196	1545	241	292	453	30	0	0
Man power	440	4435	4225	7522	7837	4032	65	30
Nitrogen	22	78	53	42	527	25	61	47
Printer	25	3124	897	1234	1067	1161	184	462
Eye mark	10	244	340	163	153	331	142	867
Thermal	0	30	30	0	0	0	0	0
Knife	210	289	528	600	990	791	2699	589
Alignment	80	192	1011	451	652	558	826	206
Mix delay	740	1698	2736	2477	2363	1511	1830	1559
Sachet unwinding	0	17	66	32	38	30	120	19
Clutch	1270	3510	2153	3808	449	1090	0	0
Valve seal	0	0	0	0	0	0	0	0
Sealing temperature	0	0	27	20	179	0	0	0
Maintenance	83304	3112	1669	10190	16566	45280	29373	2567
Kentrol	450	83	10	81	80	490	23	0
Three-way valve	158	121	60	60	40	140	68	70
Other	10952	19191	17252	23849	30189	31716	15064	7107
Total	194611	122591	98090	133033	131319	158633	131119	90660

Source: technique department, data room, and logbooks (Appendices I–F, G)

The table shows the downtime due to various reasons such as raw material shortage, planned maintenance, planned shutdown, manpower, nitrogen, printer, eye mark, thermal, knife, alignment, mix delay, sachet unwinding, clutch, valve seal, sealing temperature, and others.

The downtime in filler and packaging machines in the Hilina manufacturing industry was caused by various issues or recursion problems, such as raw material shortages, planned maintenance, and maintenance issues. The data shows that machine A had the highest downtime of 194,611 minutes, followed by machine B with 122,591 minutes. The other machines had lower downtime. It is important for companies to address these issues in order to increase equipment effectiveness and reduce downtime. For such recursion problems, there is a possible solution from the perspective of the organization; such a solution is suggested in Section 4.6 below.

4.6 Possible suggestion of all-over equipment effectiveness

Industry 4.0 technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data Analytics can help industries improve their efficiency, reduce downtime, and optimize maintenance. Here are some possible ways reason space and discuss these problems from the perspective of Industry 4.0:

Table 4.24 Recursion problems and their possible solutions

Problems	Possible reason	Possible solutions
warmth of the working environment	Failures to have filters	Adjust a smart HVAC system that can adjust temperature and humidity levels automatically based on sensor readings.
Urschel grinder oil drops, Grinder & mixer	Schedule missed, adjusting in brushes.	Use predictive maintenance algorithms to schedule maintenance before failures occur. Install sensors that can monitor oil levels and detect leaks in real-time.
The horizontal belt of a conveyor frequently spits	Signs of wear	Use computer vision and machine learning to detect signs of wear and tear on conveyor belts and automatically schedule replacements.
Thermal is not doing CIP properly	Variable frequency drive (VFD) required	used a smart control system that can adjust the frequency and voltage of the thermal's power supply automatically based on sensor readings.
Automatic filler doors are not functional.	Motors broken down	Install sensors that can detect when doors are not opening or closing properly and automatically trigger corrective actions.

Overflow at packing product hoppers	Pipe sealing rubbers are damaged.	Changing the rubbers with a new rubber and making modifications to the programming (i.e., valve opening and closing, balance in outflow) on to filler. And use machine vision and machine learning algorithms to optimize valve opening and closing and balance outflow to the filler to prevent overflow.
Dose loss of finished product	Machines dose fluctuate	Use predictive modelling and machine learning algorithms to validate machine performance and detect fluctuations in dosages that lead to the loss of finished product. and conducting machine performance validation.
Sachets dropping from the conveyors	The conveyors are not stable due to a design problem.	Use machine vision to detect when sachets are not properly positioned on the conveyor and trigger corrective actions, making the conveyors stable and making modifications to the design.
Cartons are not sealed properly.	Carton sealers need spares.	Changing the spring rollers, maintaining the side holder, and following up on the operator’s performance Use machine vision to detect when cartons are not properly sealed and trigger corrective actions. Implement a smart control system that can adjust the pressure and speed of the carton sealer automatically.
Sachet was unwinding, and Sachet busted on the porch press machine.	Poor sachet film quality	Use machine vision to detect when sachets are not properly sealed and trigger corrective actions. communicate with sachet suppliers to improve sachet quality.
Rapeseed oil holding tank being stable for too long	Oil reacts with plastic, change color	Use sensors to monitor the stability of the tank and automatically trigger maintenance when necessary. and changing the tank with a

		stainless-steel tank (until the tanker is changed with a new plastic).
Sachet unwinding delivered to the weighing	Sachets are not racked properly.	Making modifications on the conveyors and checking the counter Use computer vision to detect when sachets are not properly racked and trigger corrective actions. Implement a smart control system that can adjust the speed and position of the conveyors automatically.
The palm melting tank is not melting the palm properly	Volta thermal secondary pump failed	Practice sensors to monitor the temperature and pressure of the tank and automatically adjust the thermal's power supply to ensure proper melting.
Roaster chamber vary temperature on its 3 sections, and Sortex	Peanut defect hull, moisture, and infested	Malfunctioning heating system or lack of insulation possible solution: Check the heating system and ensure proper insulation is in place. Consider installing additional sensors to monitor temperature variations. Better quality control practices during harvesting and storage, such as proper drying of peanuts and regular inspection for infestation. Consider investing in machinery for sorting and cleaning peanuts. Regularly clean and maintain the camera lenses.
Nitrogen out of range	Moist atmosphere	Practice sensors to monitor the nitrogen levels and automatically trigger adjustments to the compressor and membranes. And cleaning the dose rods weekly
Dose fluctuation at machine B	Program trouble shooting	Practice predictive maintenance algorithms to detect and replace broken dose adjusters before they fail.

Packing machines doors are damaged	Design and material	Use materials that are more durable and resistant to wear and tear to design new closing doors (changing the machines position + side locking is recommended), repairing it
Sachet busted on the porch press machine	Poor sachet film quality	Practice computer vision to detect when sachets are not properly sealed and trigger corrective actions. Adjust sealing time parameters to improve sachet quality and check the sachet quality by changing parameters. That is sealing time
Leakage at machine A	Vertical jaw problem	Practice sensors to monitor the vertical jaw and automatically trigger maintenance when necessary. Repairing, and need preventive maintenance
The D machine dose can't be adjusted or aligned.	The dose adjuster is broken down.	a system that requires operators to verify and confirm that the dose adjuster key is properly fixed after adjusting the dose. Jaw adjustment and prediction for other
I, H, E, and F machine printer problems	Delayed service time	cleaning with solvent, and using predictive maintenance algorithms to schedule maintenance before failures occur.
A, C, and D machine leakage	Jaw problem	practice sensors to monitor the vertical jaw and automatically trigger maintenance when necessary. Implement a system that requires two people to be on the conveyors at all times.
Metal detector is alarming improperly.	Sensor malfunction	custom machine learning algorithms to optimize the sensor's sensitivity and reduce false alarms. Troubleshooting the sensor
Quality parameters, i.e., insect killers and rodent traps, are not	Irresponsible operators and a shortage of space	Use computer vision to monitor the store and ensure that quality parameters are being respected.

respected in the finished product store.		
Sachets are packed in a carton, an unacceptable loss.	The machine's dose fluctuates. It fills the required range.	Checking the machine's dose, validating the acceptable upper and lower limits, and using predictive solution and machine learning algorithms to validate machine performance and detect fluctuations in dosages that lead to loss of finished product
Thermal pressure has raised, i.e., to 5.1 above seated bar (4.0).	It worked for more than two months.	Practice sensors to monitor the thermal pressure and automatically adjust the thermal's power supply to ensure proper pressure.
The packing machine covering doors are damaged	Unsuitable design	Use materials that are more durable and resistant to wear and tear to design new coverings for doors.
Air lock doors are frequently broken down.	Improper use	Use sensors to monitor the doors and automatically trigger maintenance to open or close them when necessary. Educate operators on proper use.
All machines stopped working (power on/off).	Power fluctuation	Contacting EEPC with smart communication bases like IoT, and checking the auto-start generator sensor
After preventive maintenance is done on C, D, and E machines, not much change is observed.	The solution given was not correct.	Before disassembling, first be confident the manual is available and properly focused, and use machine vision during assembled and disassembled action on the device for each procedure.
Packing machines are not cleaned properly, causing delays in packing.	The cleaning is not approved by professionals, and mechanical system issues	Technique and quality Persons need to check and approve the cleaning effectiveness. 6S training and maintaining mechanical systems

Printer alarm bulbs are not working and are stacked.	Signal lights are damaged and stacked.	Changing and repairing signal lights
The machine cleaning and stacking procedure is taking more time than expected.	Machines are not cleaned properly when leakage occurs.	Cleaning the stacking machines efficiently when leakage occurs on every shift requires 6S training.
The double machine causes leakage of product when sealing and cutting the sachet.	The knife is too long.	Adjusting the knife length
Dose variation at the A, D, E, and B machines	Pump pressure and dose control program problems	Troubleshooting programs, maintenance of the pump, and predictive maintenance algorithms to detect and replace broken pumps and adjust dose control programs
Leakage occurs frequently, and the valve seal	eye mark configuration and sachet consistency	Changing the Teflon, checking Sachet quality with a nano checker, and using machine vision to detect when sachets are not properly sealed and trigger corrective actions communicate with sachet suppliers to improve sachet quality.
Dose adjuster key is not stable	Supervisors are not fixing it properly	Train the operators how to adjust using a digital caliper device.
The air lock doors of the powder weighing room are broken.	Rusting, absence of lubricant on the pivot, and over force	Practice sensors to monitor the doors and automatically trigger maintenance when necessary. Implement a preventive maintenance program that includes regular painting and lubrication of pivot points.

HVAC filters are changed, but the room is still too hot.	Filter problem	Use sensors to monitor the temperature and humidity levels in the room and automatically adjust the HVAC system to maintain optimal conditions.
Overflow at C packing product hoppers	Seal rubber damaged	Use sensors to monitor the seal rubber and automatically trigger maintenance when necessary.
Leakage occurs in one sachet full batch, which will be held by the customer.	Leakage	Implemented a system that includes quality checks and inspections to prevent sachet leakage.
Technicians do not perform equally while maintaining	don't have equal awareness	Implement a training program that includes both theoretical and practical training on maintenance procedures by audio visual and simulation technology
Leakage at the double packing I & J, G & H	Improperly changing sachet by operators	Inspections to prevent sachet splitting and leakage.
CIP not working as required	VFD not working	Implement a smart control system that can adjust the frequency and voltage of the CIP system automatically based on sensor readings.
Double packing machine sachet splitting problem	Sachet cognates	Use computer vision to detect when sachets are not properly connected and trigger corrective actions.
The thermal treatment pressure bar has raised	Troubleshooting	Communicating by IoT device with Nutriset experts, why it is settled 11 bar and use sensors to monitor the pressure and automatically adjust the thermal's power supply to ensure proper pressure.

Taking too much time when starting the thermal treatment	Taking too much time when heating to reach 60 ^{0}c	Taking too much time when starting the thermal treatment: Use sensors to monitor the temperature and automatically adjust the thermal's power supply to reach the required temperature more quickly.
Chain problem at B	Speed slower	Making modifications, implement a system that includes regular maintenance procedures and inspections.
UPS shutdown	Moisture while cleaning	Practice moisture detector and use sensors to monitor the environment and automatically trigger maintenance when necessary. Implement a system that requires operators to follow proper cleaning procedures.
Sachet is not packed	Machines dose fluctuate	Use machine vision to monitor the gross weight and trigger corrective actions when necessary. Implement a system that includes regular inspections and maintenance procedures.
N_2 Compressor interruption	Hose busted	Use sensors to monitor the hoses and automatically trigger maintenance when necessary. Implement a system that requires operators to follow proper ON/OFF procedures.
E dose variation	Dose variation	Practice predictive maintenance algorithms to detect and replace broken pumps and adjust dose control programs.
Ink from a printer contaminates our product.	Misuse and malfunction	Implement a training program that educates operators on the proper use of printers and cleaning procedures.
Vertical, horizontal leakage, and seal temperature	Sachet quality	Using the trend expected, what types of maintenance are occurring? IoT devices are used to monitor the performance of the motors and detect any abnormalities or changes in

		performance. By analysing the data collected from the sensors, it's possible to identify the root cause of the leakage, seal it, and take corrective action before it causes major damage.
Clutch, grease on the conveyors	Leakage from motors	Use materials that are more durable and resistant to leakage to design the gear or seal. a sensor that can detect when the clutch is not functioning properly and automatically trigger corrective actions. and practice predictive maintenance algorithms to schedule maintenance before failures occur. Using a cleaning system that can remove grease from the conveyors periodically and prevent slippage Use machine vision and machine learning to detect signs of wear and tear on the conveyors and automatically schedule replacements. Using automation and digital monitoring, the amount of grease or lubricants that are used can be monitored and adjustments made to ensure that the correct amount is applied. This minimizes waste and avoids over lubrication, which may lead to problems like clogging.
Three-way valve	Over and under flow,	The valve could be equipped with sensors that monitor its performance in real-time. By analyzing the data collected from the sensors, it's possible to detect any abnormalities or changes in performance and take corrective action before it causes major damage. Adjust the valve opening and closing automatically based on sensor readings and product flow. And practice predictive modeling

		and machine learning algorithms to optimize valve performance and prevent overflow or underflow. Early detection of valve problems can allow for proactive maintenance resulting in reducing downtime.
Kentrol refers to a smart sensor or device that monitors the performance of mechanical systems.	mechanical system interruption	Use a smart control system that can adjust the speed and direction automatically based on sensor readings and product demand. Practice machine vision and machine learning algorithms to monitor product quality and detect defects or anomalies. By integrating Kentrol with other IoT devices, it's possible to collect real-time data on the health of mechanical systems and detect potential issues before they become major problems.
Pre-blend mixer product temperature is declining.	Heater failed	Use the heater and automatically trigger maintenance when necessary.

The above table 4.24 provides a list of various problems that can occur in an equipment facility and their possible root causes and solutions. The problems range from equipment failures to operator errors and environmental factors. Using trend-expected failure, decision-making tools, pattern recognized trained with data, implementing regular preventive, predictive, and corrective maintenance procedures, training programs for operators, and using more durable materials can help address some of the root causes of these problems. The overall idea is to identify and address the root causes of these problems in order to minimize downtime, reduce waste, and increase equipment effectiveness in the production facility. The table also suggests some possible solutions that can leverage industry 4.0 technologies such as smart control systems, sensors, machine vision, machine learning, corrective, preventive and predictive maintenance, integrating sensors and IoT devices with the machines, it's possible to monitor the performance of the system in real-time and detect any abnormalities. Additionally, AI-powered predictive maintenance algorithms analyze the big data collected from the sensors to predict when maintenance is required and prevent downtime, breakdown, speed and quality losses of overall equipment effectiveness. These solutions can help reduce recursion and other unknown problems on overall equipment effectiveness and finally can help to enhancing organizational OEE.

The Hilina Enriched Energy Food Manufacturing Industry can leverage Industry 4.0 tools to address the problems related to leakage, sealing, shutdown, dose variation, overflow and underflow, Sachet cognates and unwinding, eye mark issue, clutch, grease on the conveyors, leakage from motors and filler dose, mechanical and electrical system fluctuation and interruption. Overall, cutting edge technologies can help industries improve the availability, quality, and performance of their mechanical systems by providing real-time data and insights. By leveraging AI-powered predictive maintenance algorithms and IoT devices, it's possible to optimize machine availability, reduce speed loss, and improve quality.

In summary, Industry 4.0 technologies and tools can provide the Hilina Enriched Energy Food Manufacturing Industry with the tools to address the problems related to recursion and other unknown problems. The use of advanced technologies like IoT, big data analytics, automation, and predictive maintenance can lead to fewer equipment breakdowns and an increase in the overall equipment efficiency and productivity, resulting in better OEE scores.

4.6.1 Positive impact of Industry 4.0 for OEE improvement

The potential influence of Industry 4.0 on manufacturing processes' OEE is enormous, as you seen above table 4.24. A decrease in downtime, greater quality, increased effectiveness of equipment, and lower costs are all results of improved OEE. The following are some concrete ways that industry 4.0 technologies affect OEE:

- Predictive maintenance: technology and tools, such as machine learning algorithms, are utilized to anticipate when maintenance work on equipment is necessary before it breaks down and speed and quality losses occur. Downtime decreased or speed and quality increased; consequently, OEE will be raised by identifying and resolving potential problems before they become serious ones.
- Monitoring in real time: Industry 4.0 technologies and tools offer real-time monitoring of equipment status and operation. Because of this, operators respond to problems as they develop more rapidly, cutting downtime, speed, and quality loss, which then raises OEE.

- Data analytics is industry 4.0 technology used to examine data from manufacturing processes, find trends, and gain insights that can be applied to improve output and cut down on downtime and speed losses.
- Automation: technology like robotics and automation helps lower manual labor and mistakes, enhancing effectiveness and lowering downtime, speed, and quality losses.

Manufacturers evaluate the effectiveness of their operational processes and spot areas for improvement by calculating OEE. OEE assists producers in locating and eliminating production bottlenecks, maximizing equipment effectiveness, and improving all aspects of equipment effectiveness.
So due to this impact, there will be the possibility of reducing the downtime, speed, and quality loss of the auxiliary grand machine, which will change the percentage enhancement of overall equipment effectiveness (OEE) of the Hilina energy-enriched food manufacturing industry based on the possible solutions provided in Table 4.23. It is important to note that exact percentage values cannot be provided without exact solutions, situations, events, and information about the current and future OEE performance of the Hilina energy-enriched food manufacturing industry. However, it is possible to analyse each solution and provide potential benefits and reasoning based on industry best practices (McRoberts, 2018), (Bashir, 2022). These possible solutions and their possibility of changing the current OEE of the Hilina energy-enriched food manufacturing industry are listed below:

Applying a smart HVAC system that can automatically adjust temperature and humidity levels based on sensor readings can improve OEE by creating an optimal environment for production, control overflow and under flow, sealing temperature, and Sachet cognates. This can prevent product defect, reduce energy consumption, and enhance worker comfort and effectiveness. According to a study by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), proper temperature and humidity control can significantly impact product quality and manufacturing efficiency (AmericanSocietyofHating, 2018).

By using predictive maintenance and real-time monitoring algorithms and installing sensors to monitor oil levels, detect vertical and horizontal leaks, seal, jaw and clutch cracking in real-time, maintenance activities can be scheduled proactively, reducing unplanned downtime, speed and quality losses and increasing OEE. This study conducted company has shown that predictive maintenance can reduce maintenance costs by up to 30% and improve equipment availability, performance and quality by 20% (Kinsey, 2018), (McRoberts, 2018), (Bashir, 2022).

Deploying machine vision and learning to detect signs of wear and tear on conveyor belts, three-way valve, Kentrol, dose, printer issues, and automatically schedule replacements can improve OEE by minimizing unexpected breakdowns and optimizing maintenance schedules. A study by IBM highlights the use of computer vision and machine learning for predictive maintenance, resulting in a 10% reduction in downtime and a 25% decrease in maintenance costs (IBM, 2017). Smart control system for thermal power supply that adjusts alignment, nitrogen compressor, porch press machine, the frequency and voltage of the thermal power supply based on sensor readings can optimize energy consumption and equipment performance, thereby enhancing OEE (Abeyratne, 2014), (McRoberts, 2018).

Installing sensors that can detect when air lock doors are not opening or closing, mechanical system properly and automatically triggering corrective actions can minimize machine operation disruptions and improve OEE. While their specific studies directly addressing this solution, similar sensor-based systems in industries have shown positive impacts on operational effectiveness and equipment reliability.

It is important to note that the provided solutions are hypothetical and their actual impact on OEE in the Hilina energy-enriched food manufacturing industry would depend on various factors such as the current and future state of operations, equipment condition, and implementation strategy. Conducting a thorough analysis and piloting these solutions in a controlled environment would be necessary to determine the precise percentage enhancement in OEE.

4.6.1.1 Estimated improved OEE over production days based on possible solution

Raw data is used as an input when calculating the OEE improvement over production days. According to (Abeyratne, 2014), (Kinsey, 2018), and (IBM, 2017), a 25 to 30 percent reduction in maintenance cost, a 10 percent reduction in downtime, a 5 percent reduction in speed loss, and a 5 percent reduction in quality, the total reduction in OEE losses is 20 percent (the total increment in OEE is 20 percent) on the filler and packaging machines. Since, according to Table 4.24, the possibility of recursion problems occurring is 70 percent on the filler and packaging machines, these reductions have a much greater effect on the filler and packaging machines than auxiliary machines. But according to the general reduction of the recursion problem, the auxiliary machine takes 15 percent, which is a 5 percent reduction in downtime, a 5 percent reduction in speed loss, and a 5 percent reduction in quality. Therefore, the total reduction of the auxiliary machine's OEE loss is 15 percent (the total increment in OEE is 15 percent).

Therefore, the estimation analysis of auxiliary grand machines in Hilina's manufacturing industry is in Table 4.19 (auxiliary machine) and Table 4.20 (filler and packaging machine). The possible improvement estimation of OEE are as follows:

Estimated improved OEE for the auxiliary machines based on the possibility of a solution

The weighted average of the availability, performance, and quality percentages for all ten machines will be after reducing the OEE by 15 percent on each machine (reducing downtime by 5 percent or increasing availability by 5 percent, reducing speed by 5 percent or increasing performance by 5 percent, and reducing quality by 5 percent or increasing quality by 5 percent), the total reduction on the auxiliary machine is 15 percent, or the OEE is increased by 15 percent, since the auxiliary machine 4.24 possibility solution covers 30 percent.

Table 4.25 Auxiliary machine estimated improved OEE

Auxiliary machine	Availability	Performance	Quality	OEE
Roaster machine	87.41%	96.43%	90.20%	76.03%
Sortex machine	87.91%	96.21%	95.51%	80.78%
Pre-Blend machine	87.29%	94.12%	99.44%	81.70%
Grinder & Mixer A	86.58%	92.17%	99.50%	79.40%
Blend machine	86.60%	94.44%	99.18%	81.11%
Grinder & Mixer B	86.25%	91.89%	99.20%	78.62%
Vacuum pump	87.92%	95.42%	100.00%	84.27%
Thermal treatment	88.38%	96.22%	100.00%	85.29%

For the overall OEE of the factory, we need to combine the availability, performance, and quality percentages for all the machines and then calculate the weighted average OEE. First, we need to calculate the weighted average of the availability, performance, and quality percentages for all machines. To do this, we multiply each percentage by the weight of the corresponding machine (i.e., the proportion of time it takes in the overall process). Then, we sum up these products across all machines. For the auxiliary machine weighted average of the availability, performance, quality percentages, and OEE, we use the following formula:

$$\text{Weighted Availability} = \frac{(A1 * W1) + (A2 * W2) + \ldots + (An * Wn)}{\text{Total weight}} \ldots.\text{(from equ 2.10)}$$

$$\text{Weighted Performance} = \frac{(P1 * W1) + (P2 * W2) + \ldots + (Pn * Wn)}{\text{Total weight}} \ldots \text{(from equ 2.11)}$$

$$\text{Weighted Quality} = \frac{(Q1 * W1) + (Q2 * W2) + \ldots + (Qn * Wn)}{\text{Total weight}} \ldots\ldots\ldots \text{(from equ 2.12)}$$

$$\text{OEE} = \text{weighted averages of the Availability} * \text{weighted averages Performance} * \text{weighted averages Quality} \ldots\ldots\ldots\ldots\ldots \text{(from equ 2.13)}$$

Were

A1, A2, ..., A8 are the Availability percentages for each machine,

P1, P2, …., P8 are Performance percentages for each machine

Q1, Q2, …., Q8 are Quality percentages for each machine

W1, W2, ..., W8 are their weights.

The calculation of the OEE involves weighting each of these factors according to their relative importance and then multiplying them together to obtain a single score. A higher score indicates greater efficiency and effectiveness, while a lower score indicates room for improvement (from an interview with experts). The wight is depended on to do operations in total coverage out of 100 in the factory; the Hilina enriched food manufacturing company gives these wights on its distribution, i.e., the auxiliary machine is 50% wight, the filler and packaging machine is 13% wight, and the product in and out is 37% wight cover including utility. The pre-blend and blend machines are equal in weight, which is W3, W5, which is equal to 10 (ten) in weight because these machines do additional tasks that add additives to their processes, but the remaining machines, Sortex, Grinder and mixer A B, vacuum pump, and thermal machine, which are W1, W2, W4, W6, W7, and W8, are equal to 5 (five) in weight.

Using the data in the given table, we can calculate the weighted averages for availability, performance, and quality as follows:

$$\text{Weighted Availability}$$

$$= \frac{\begin{pmatrix}(87.41\% * 5) + (87.91\% * 5) + (87.29\% * 10) + (86.58\% * 5) + \\ (86.10\% * 10) + (86.60\% * 5) + (87.92\% * 5) + (88.38\% * 5)\end{pmatrix}}{50}$$

$$= 87.29\%$$

$$\text{Weighted Performance}$$

$$= \left(\frac{\begin{matrix}(96.43\% * 5) + (96.21\% * 5) + (94.22\% * 10) + (92.17\% * 5) + \\ (94.44\% * 10) + (91.89\% * 5) + (95.42\% * 5) + (96.22\% * 5)\end{matrix}}{50}\right)$$

$$= 94.61\%$$

$$\text{Weighted Quality}$$

$$= \frac{\begin{pmatrix}(90.20\% * 5) + (95.51\% * 5) + (99.44\% * 10) + (99.50\% * 5) + \\ (99.18\% * 10) + (99.18\% * 5) + (100.00\% * 5) + (100.00\% * 5)\end{pmatrix}}{50}$$

$$= 98.00\%$$

Now, we can calculate the overall OEE by multiplying the weighted averages of the Availability, Performance, and Quality

$$\textbf{OEE auxilary machine}$$

$$= \textbf{weighted averages of the Availability} * \textbf{weighted averages Performance} * \textbf{weighted averages Quality} = \mathbf{A} * \mathbf{P} * \mathbf{Q} \ldots\ldots(\textbf{from equ 2.13})$$

$$= \mathbf{87.29}\% * \mathbf{94.61}\% * \mathbf{98.00}\%$$

$$= \mathbf{80.94}\%$$

This analysis shows that it can be concluded that the OEE (Overall Equipment Effectiveness) of the auxiliary machines in the Hilina Enriched Energy Manufacturing Industry is generally quite high because it increases OEE from 79.64 to 80.94 percent, with most machines showing OEE values in the range of 79.4 percent to 84.29 percent. Overall, based on this analysis, the Hilina Enriched Energy Manufacturing Industry possibility seems to be performing well in terms of OEE for the auxiliary machines, but continuous improvement is necessary to sustain and increase this performance.

<u>Estimated improved OEE for the filler and packaging machines, based on the possibility of a solution</u>

For the filler and packaging machines, we need to calculate the weighted average of the availability, performance, and quality percentages for all ten machines. After reducing the OEE by 20 percent on each machine (reduce downtime by 10 percent or increase availability by 10 percent, reduce speed by 5 percent or increase performance by 5 percent, and reduce quality by 5 percent or increase quality by 5 percent), the total reduction on filler and packaging machines is 20 percent, or the OEE increases by 20 percent.

Table 4.26 Estimated improved OEE for filler and packaging machines

Filler & packaging	Availability	Performance	Quality	OEE
A	51.08%	56.45%	95.10%	27.42%
B	74.94%	65.89%	94.38%	46.60%
C	85.17%	72.21%	88.98%	54.72%
D	77.54%	45.52%	95.53%	33.72%
E	80.18%	70.46%	92.98%	52.53%
F	67.23%	70.22%	91.53%	43.21%
G	79.17%	69.41%	101.27%	55.65%
H	79.17%	69.41%	87.68%	48.18%
I	82.83%	69.41%	101.27%	58.22%
J	82.83%	69.41%	101.27%	58.22%

$$\text{Weighted Availability} = \frac{(\text{A1} * \text{W1}) + (\text{A2} * \text{W2}) + \ldots + (\text{An} * \text{Wn})}{\text{Total weight}} \ldots\ldots \text{(from equ 2.10)}$$

$$\text{Weighted Performance} = \frac{(\text{P1} * \text{W1}) + (\text{P2} * \text{W2}) + \ldots + (\text{Pn} * \text{Wn})}{\text{Total weight}} \ldots. \text{(from equ 2.11)}$$

$$\text{Weighted Quality} = \frac{(\text{Q1} * \text{W1}) + (\text{Q2} * \text{W2}) + \ldots + (\text{Qn} * \text{Wn})}{\text{Total weight}} \ldots\ldots\ldots.. \text{(from equ 2.12)}$$

$$\begin{aligned}&\text{OEE auxilary machine}\\&= \text{weighted averages of the Availability} * \text{weighted averages Performance}\\&* \text{weighted averages Quality} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (\text{from equ } 2.13)\end{aligned}$$

Were, A1, A2, ..., A10 are the Availability percentages for each machine, P1, P2, …., P10 are Performance percentages for each machine, Q1, Q2, …., Q10 are Quality percentages for each machine, W1, W2, ..., W10 are their weights.

The filler and packaging machine are dependent on their status. The C and E filler machines are equal in weight, which is W3, W5, which is equal to 2 (two) in weight because these machines are effective in their processes, but the remaining machines, A, B, D, F, G, H, I, and J filler machines, which are W1, W2, W4, W6, W7, W8, W9, and W10, are equal to 1 (one) in weight since the machines obviously host external downtime issues, which is a break for a reason.

$$\text{Weighted Availability}$$
$$= \frac{\begin{pmatrix}(51.08 \text{ x } 1) + (74.94 \text{ x } 1) + (85.17 \text{ x } 2) + (77.54 \text{ x } 1) + (80.18 \text{ x } 2) + \\ (67.23 \text{ x } 1) + (79.17 \text{ x } 1) + (79.17 \text{ x } 1) + (82.83 \text{ x } 1) + (82.83 \text{ x } 1)\end{pmatrix}}{13}$$
$$= 76.01\%$$

$$\text{Weighted Performance}$$
$$= \frac{\begin{pmatrix}(56.45 \text{ x } 1) + (65.89 \text{ x } 1) + (72.21 \text{ x } 2) + (45.52 \text{ x } 1) + (70.46 \text{ x } 2) + \\ (70.22 \text{ x } 1) + (69.41 \text{ x } 1) + (69.41 \text{ x } 1) + (69.41 \text{ x } 1) + (69.41 \text{ x } 1)\end{pmatrix}}{13}$$
$$= 65.84\%$$

$$\text{Weighted Quality}$$
$$= \frac{\begin{pmatrix}(95.10 \text{ x } 1) + (94.38 \text{ x } 1) + (88.98 \text{ x } 2) + (95.53 \text{ x } 1) + (92.98 \text{ x } 2) + \\ (91.53 \text{ x } 1) + (100.00\text{x } 1) + (87.68 \text{ x } 1) + (100.00 \text{ x } 1) + (100.00 \text{ x } 1)\end{pmatrix}}{13}$$
$$= 95.00\%$$

By substituting the weighted averages of availability, performance, and quality back into the formula for OEE, we can calculate the overall OEE for the filler and packaging machines: Now, we can calculate the overall OEE by multiplying the weighted averages of availability, performance, and quality.

$$\mathbf{OEE\ filler\ \&\ packaging}$$

$$= \mathbf{weighted\ averages\ of\ the\ Availability} * \mathbf{weighted\ averages\ Performance} * \mathbf{weighted\ averages\ Quality} = \mathbf{A} * \mathbf{P} * \mathbf{Q} \ldots\ldots..(\mathbf{from\ equ\ 2.13})$$

$$= \mathbf{76.0\ 1}\% * \mathbf{65.84}\% * \mathbf{95.0\ 0}\%$$

$$= \mathbf{47.84}\%$$

With the estimated increment of the filler and packaging machine, it seems like the Hilina Enriched Food Manufacturing Industry has room for improvement in terms of overall equipment effectiveness (OEE) for the filler and packaging machine category, as the OEE of the overall machines ranges from 33.46 percent to 47.84 percent. This change is a good indicator of showing good change, and with repetition again and again with continually small and small changes, the company achieved a good standard on its levels of accomplishment. Overall, the Hilina-enriched food manufacturing industry's performances will be quite good for auxiliary machines, showing a good change and great profit on its estimation value of filler and packaging machines.

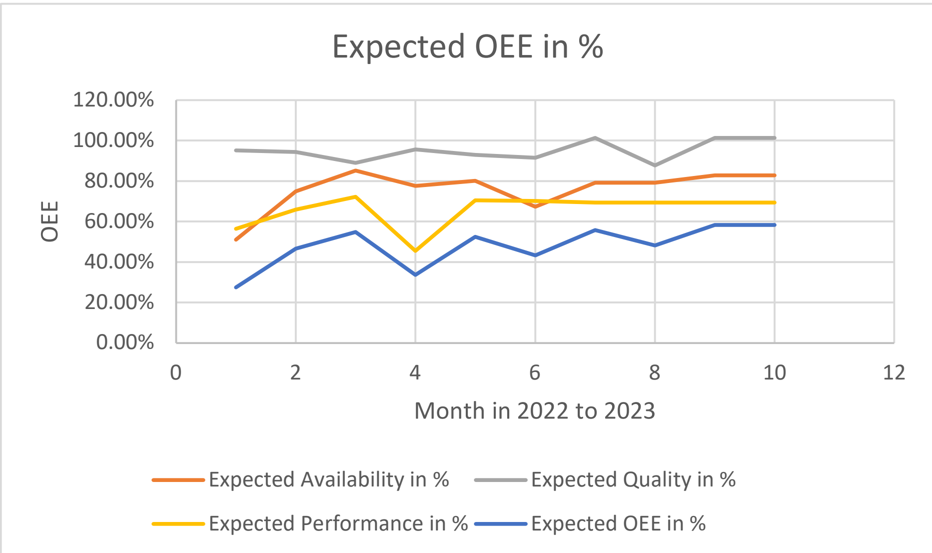


Figure 4.36 Expected filler and packaging machine OEE trend

Therefore, The overall effectiveness of the Hilina manufacturing industry (auxiliary grand machine or auxiliary machine plus filler and packaging)

$$\mathbf{OEE\ Hilina\ manufacturing\ factory} = \mathbf{OEE}$$

$$= \mathbf{weighted\ averages\ of\ the\ Availability} * \mathbf{weighted\ averages\ Performance} * \mathbf{weighted\ averages\ Quality} \ldots\ldots\ldots\ldots\ldots (\mathbf{from\ 2.13})$$

Were

Weighted averages of the Availability= {(Weighted averages of the Availability auxiliary machine*50 + Weighted averages of the Availability of filler and packaging machine*13)} / 63….., (from 2.10)

$$= \frac{\{(87.29\% * 50) + (76.01\% * 13)\}}{63}$$

$$= 84.96\%$$

Weighted averages of the performance = (Weighted averages of the performance of the auxiliary machine*50 + Weighted averages of the performance of the filler and packaging machine*13) / 63...., (from 2.11)

$$= \frac{\{(94.61\% * 50) + (65.83\% * 13)\}}{63}$$

$$= 88.67\%$$

Weighted averages of the quality = (weighted averages of the quality of the auxiliary machine*50 + weighted averages of the quality of the filler and packaging machine*13) / 63......, (from 2.12)

$$= \frac{\{(98.00\% * 50) + 95.00 * 13)\}}{63}$$

$$= 97.38\%$$

$$\mathbf{OEE} = \mathbf{weighted\ averages\ of\ the\ Availability} * \mathbf{weighted\ averages\ Performance} * \mathbf{weighted\ averages\ Quality} \ldots\ldots\ldots\ldots\ldots (\mathbf{from\ 2.13})$$

$$= \mathbf{84.96}\% * \mathbf{88.67}\% * \mathbf{97.38}\%$$

$$= \mathbf{73.36}\%$$

Overall, possibility analysis due to possibility solution is, the OEE for Hilina's manufacturing factory is 73.36 percent, which means that the factory is using 73.36 percent of its manufacturing time effectively. This is a good score compared to the ideal OEE of world-class, and company standard which indicates that there are many possible solutions for each loss and inefficiencies in the manufacturing process. The analysis also shows that the auxiliary machines have a higher OEE than the filler and packaging machines, which means that the latter machines need more improvement in terms of availability, performance, and quality

Table 4.27 Overall estimated improved OEE of the auxiliary grand machine

Auxiliary machine	Availability (in%)	Performance (in%)	Quality (in%)	OEE (in %)
Auxiliary machine average weight of	87.29%	94.61%	98.00%	80.93%
Filler and packaging machine average weight	76.01%	65.84%	95.00%	47.84%
Auxiliary grand machine Average weight of	84.96%	88.67%	97.38%	73.36%
OEE of the factory		73.36%		

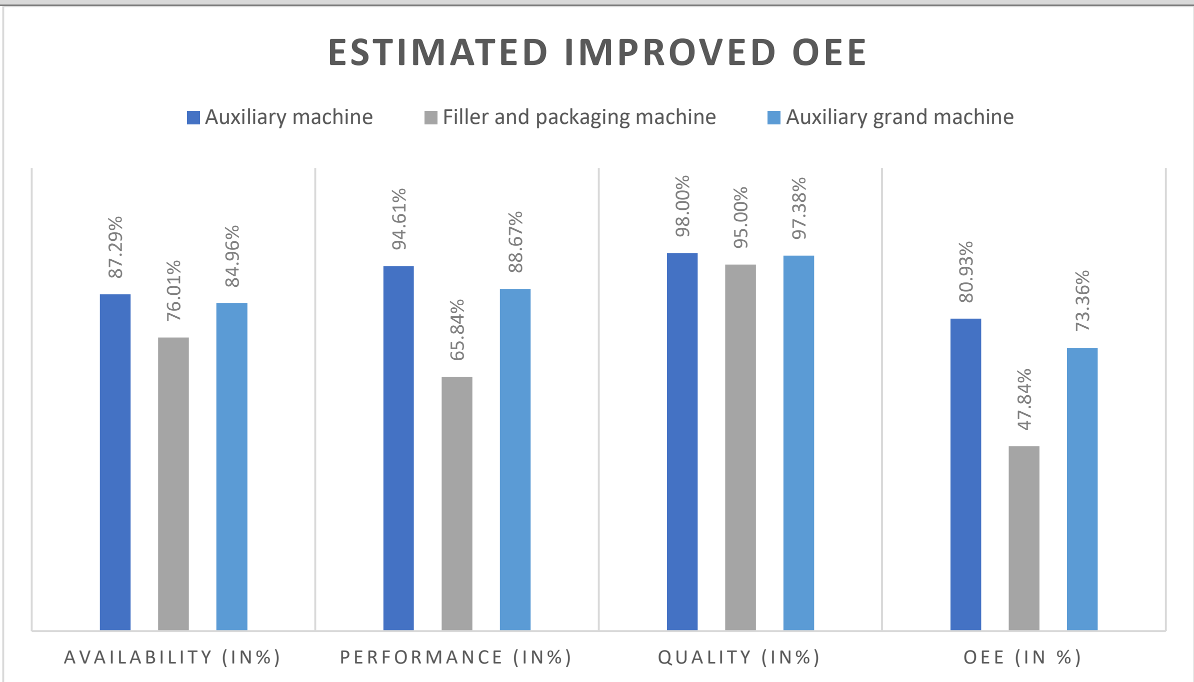


Figure 4.37 Overall possibility of an estimated improved OEE of the auxiliary grand machine

4.7 Summary

In summary, OEE performance is improved by Industry 4.0 technologies and tools through big data analysis. Advanced analytics are used in data-driven OEE optimization to identify the primary reasons for OEE loss across the three OEE drivers of quality, performance, and availability. A case study by Hilina Energy Enriched Food Manufacturing Industry, which analyzes an increase in OEE from 68.34 percent to 73.36 percent through the use of fault detection root cause possibility solution for recursion problem, is one illustration of the successful application of Industry 4.0 in OEE optimization. Equipment effectiveness and decision-making in manufacturing can all be enhanced by other Industry 4.0 technologies like, the Internet of Things, machine learning, and vision to suggest possible solutions for root causes of downtime, speed, and quality losses. Overall, Industry 4.0 tools and data-driven decision-making have great potential to optimize OEE and manufacturing processes by suggesting possible solutions for observed current problems.

Chapter five

5 Conclusion and recommendation

5.1 Conclusion

This study focused on improving system metrics, and its investigation began with auxiliary grand equipment, particularly filling and packaging machinery, followed by data analysis and findings regarding the use of Industry 4.0 to increase OEE. In the answer, it is explained in detail how Industry 4.0 technologies like big data analytics and computer learning algorithms are applied to enhance OEE performance through data analysis and decision-making. To enhance OEE performance, the three OEE drivers of availability, performance, and quality are employed to pinpoint the root causes of OEE loss. Utilize Industry 4.0 technologies like big data analytics, smart devices, machine learning and vision, and the Internet of things to make data-driven decisions that can enhance OEE performance.

Data-driven decision-making often helps companies with downtime reduction, speed and quality losses in machinery, and OEE optimization when using Industry 4.0 technologies. Some notable outcomes of OEE improvement through Industry 4.0 processes are as follows:

- OEE is improved through root-cause failure analysis, problem detection, and solution-giving.
- predictive analytics to reduce losses in speed, quality, and downtime
- improved quality control through ongoing monitoring and assessment
- improved labor productivity through automation and optimization

In order to support decision-making and efforts toward continuous improvement, these findings are typically presented via data visualizations, scorecards, and performance dashboards. A possible solution for improving OEE through the usage of Industry 4.0 was developed as part of this study's overall goal, which was to explore and improve the existing overall equipment effectiveness (OEE) trend of auxiliary large machines in Hilina's energy-enriched food manufacturing industry. This emphasizes how crucial overall equipment effectiveness (OEE) is as a performance measure for the manufacturing industry framework. The study identifies criteria for measuring equipment effectiveness, looks into the existing OEE trend, and suggests potential ways to improve OEE using Industry 4.0 technology. Department logbooks, technical apps, and smart devices were among the sources of primary and secondary data that were used in the study. The data analysis tells that the filler and packaging machine, with an actual speed below design capacity, suffers from the greatest downtime, quality, and speed losses. According to the report, Industry 4.0 techniques like IoT, and big data analytics can help to increase quality, lessen speed loss, and decrease downtime. The paper also suggests frequent inspections, preventive maintenance measures, and realizing potential remedies for auxiliary grand machine recursion issues. Overall, this study offers insightful information on the prospective advantages of Industry 4.0 technologies for raising OEE and boosting manufacturing processes. The most efficient methods for integrating these concepts into industrial processes require further study.

Ultimately, the improvement estimation diagram for the Hilina energy-enriched food manufacturing company was developed in a thorough manner and in accordance with the proposed OEE system using Industry 4.0, which saw a slight increase to 68.34 percent to 73.36 percent through a possible potential solution for observed issues.

5.2 Recommendation

The recommendation can be made both specifically for Hilina's energy-enriched food production industry and more generally to improve overall equipment effectiveness (OEE).

5.2.1 General recommendation

Based on the findings of the research, the following general recommendations are forwarded:

- First, this research uses literature review, machine manual, experts' opinion, smart device, logbooks, observation, SCADA as sources of data in technique, production, quality, research and development department, management staff and other workers. Due to this Industry 4.0 technologies like automation, connectivity, and data analytics are taken into account for improving OEE. This can be done by installing sensors to monitor equipment and automatically initiate maintenance when necessary. Predictive maintenance algorithms can also be used to reduce maintenance costs by 30% and identify and replace malfunctioning equipment before it fails. A smart system can also be utilized to automatically alter humidity, viscosity, temperature, and alignment based on sensor inputs.
- Second, Industry 4.0 best manufacturing practices (BMP) like predictive maintenance algorithms and smart systems were executed to further improve OEE. This can be accomplished by modifying and keeping up control programs, employing predictive modeling and machine learning algorithms to assess machine performance, and identifying changes that result in final product loss.

- Third, to ensure that effective OEE deployment is successful, employee involvement in problem-solving and improvement activities is encouraged. Exercise programs that teach users how to handle tools and clean up after themselves can help with this.
- Utilizing real-time monitoring, data analytics, automation, and predictive maintenance can aid in seeing possible issues before they become critical, decreasing downtime, speed loss, and quality loss, ultimately leading to a rise in OEE.
- To further enhance maintenance practices, frequent inspections, preventative maintenance techniques, and training programs could be introduced. The study discovered that by addressing the underlying causes of equipment losses and finding areas for improvement, the application of industry 4.0 technologies like automation, connectivity, and data analytics may considerably increase OEE.
- In order to further improve OEE, the report also suggests using best manufacturing practices (BMPs), such as predictive maintenance algorithms and smart systems.
- Finally, in order to maintain the target level of OEE and discover opportunities for further improvement, the organization regularly monitors and assesses the process. This can be done by employing pattern recognized trained with data to verify machine performance, big data analytics to identify patterns, and future prediction. loss due to downtime due to predicted decline of 10 percent.

5.2.2 Contextual recommendation

Based on the findings of the research, the following the particular circumstances surrounding Hilina's energy-enriched food manufacturing recommendations are forwarded:

- The company focuses on finding solutions to the reoccurring issues found in the study, such as modifying smart systems, utilizing predictive maintenance algorithms, putting in place smart control systems, and employing machine learning and vision algorithms.
- To help employees develop their abilities and knowledge of employing OEE, the corporation is also considering investing in fitness programs for their staff.
- To enable real-time monitoring and data analytics, the organization is considering investing in smart manufacturing, sensor, and IIoT devices.
- To ensure prompt maintenance and the resolution of equipment problems, the company also developed a BMP-based work scheduling and maintenance planning system.

- In order to guarantee user acceptability and the successful deployment of industry 4.0 technologies and processes, the organization considers performing user exercises and managing the change process.
- Finally, the company regularly assesses the process to make sure the desired OEE level is maintained and to spot areas that could use improvement.

Using industry 4.0, or latest BMP-based work scheduling and maintenance planning, and employee involvement in problem-solving and improvement activities, Hilina's energy-enriched food manufacturing industry may dramatically increase OEE. The company take these suggestions into account to improve the overall effectiveness of their equipment.

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APPENDIX

Appendix I: Manuscript

Paper Title:

Investigate the current OEE trend in manufacturing industry and propose possible solutions for enhancing OEE using Industry 4.0 approaches: A Case Study of Hilina Energy-Enriched Foods Manufacturing Industry

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Abstract:

This paper presents a case study of Hilina Energy-Enriched Foods Manufacturing Industry, which explores the use of Industry 4.0 technologies to enhance Overall Equipment Effectiveness (OEE) and improve manufacturing operations. The study aims to investigate the current OEE trend in manufacturing industry, and propose possible solutions for enhancing OEE through the use of Industry 4.0 technologies. The paper uses a mixed-methods approach, including both qualitative and quantitative data collection and analysis with the aid of advanced analytics techniques and big data (pattern recognized trained with data) applications. The data analysis identifies the biggest losses occurring at auxiliary grand machines, especially the filler and packaging machines, resulting in a current actual OEE of only 33.46%. However, the remaining auxiliary machines have an OEE of 79.64%, giving an overall OEE of 68.34%. The study suggests that Industry 4.0 technologies such as IoT, AI, and big data analytics can help improve reduce downtime, speed and quality loss, and enhance OEE.

Key word: OEE, Industry 4.0, big data, root cause analysis

Introduction:

Overall equipment effectiveness (OEE) is a type of effective excellency equipment system of measurement used to measure the overall effectiveness of equipment or machinery and plays an important role in achieving and sustaining effective process in organizations achievement (Sharma, 2019). According to (Shin, 2018), OEE can be used to measure the productivity of a machine as it takes into account the availability, performance rate, and quality rate.

In recent years, the manufacturing industry has witnessed a significant shift towards Industry 4.0 technologies, which are transforming traditional manufacturing processes through the integration of cyber-physical systems, the Internet of Things (IoT), and advanced analytics. The motivation behind this transformation is to enhance productivity, improve efficiency, and reduce downtime, ultimately leading to a reduction in manufacturing costs and an increase in profitability (Pereira, 2017).

This paper presents a case study of Hilina Enriched Foods Manufacturing Industry, which employs Industry 4.0 technologies to enhance Overall Equipment Effectiveness (OEE) and improve manufacturing operations. The study aims to investigate the current OEE trend in the manufacturing industry and proposes possible solutions for enhancing OEE through the use of Industry 4.0 technologies. By using a mixed-methods approach, including both qualitative and quantitative data collection and analysis, with the aid of advanced analytics techniques and big data (pattern recognized trained with data) applications.

The data analysis identifies the biggest losses occurring at auxiliary grand machines, especially the filler and packaging machines, resulting in a current actual OEE. Auxiliary grand machines are an essential component of a manufacturing line. For the efficient and effective operation of the machines, it is important to have reliable auxiliary grand machines. The effectiveness of auxiliary grand machines has been a subject of research over the years. This literature review presents a discussion of equipment effectiveness metrics for the effective operation of auxiliary grand machines (Subramanian, 2015). By using the industry 4.0 approach instead of other approaches like lean tools, organizations can more effectively enhance the effectiveness of their equipment and achieve maximum efficiency.

This paper contributes to the existing literature by presenting a study that highlights the effectiveness of Industry 4.0 technologies in improving manufacturing operations. The findings of this study have important implications for manufacturing industries, highlighting the potential benefits of Industry 4.0 technologies for enhancing effectiveness, reducing downtime, speed, and quality loss, and optimizing manufacturing operations.

The manufacturing industry is undergoing a significant transformation with the initiation of Industry 4.0 technologies (Herrmann, 2017).. These technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data Analytics, are revolutionizing the way manufacturing companies operate (Santos, 2018). One of the critical performance indicators for the industry 4.0 framework is Overall Equipment Effectiveness (OEE), which measures the efficiency and effectiveness of manufacturing equipment (Sipica, 2021).

Literature Review:

The review provides an overview of the OEE, and industry 4.0 framework and its potential benefits for manufacturing companies, also, highlights the importance of OEE as a critical performance indicator for the industry 4.0 framework and discusses the various factors that affect OEE.

Moreover, explores the use of Industry 4.0 technologies such as IoT, AI, and Big Data Analytics to improve OEE and reduce downtime, speed and quality loss. The concept of Industry 4.0, also known as the fourth industrial revolution, has been gaining significant attention in recent years due to its potential to revolutionize traditional manufacturing processes through the integration of advanced technologies. The application of Industry 4.0 technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, can help manufacturers achieve greater productivity, improve efficiency, and reduce costs (Kagermann, 2013), (Rüßmann, 2015). Big data analytics improve OEE by collecting and analyzing large amounts of significant data from various sources to identify patterns and trends to improve equipment A, P, Q, and efficiency, predict equipment failures, and identify opportunities for maintenance and optimization, leading to increased uptime and effectiveness, ultimately driving growth (Mariani, 2022). According to a study by (Ahmed, 2022), (Alizadehsalehi, 2020), Industry 4.0 technologies such as the Internet of Things (IoT), Big Data Analytics, and Artificial Intelligence (AI) can be used to enhance root cause analysis (RCA) in manufacturing industries. The study assesses the role of Industry 4.0 in RCA and its ability to improve OEE through the quick identification and elimination of the root cause of problems and prevention of equipment failures. An increase in the effectiveness of the RCA techniques through the incorporation of Industry 4.0 is supported by the study conducted (Morgan, 2021) , (Gao, 2020).

Several studies have investigated the use of Industry 4.0 technologies in manufacturing operations and their effectiveness in enhancing Overall Equipment Effectiveness (OEE). A study by (Kagermann, 2013) highlights the importance of Industry 4.0 in transforming traditional manufacturing systems into smart factories, resulting in increased productivity and efficiency. Another study by (Kache, 2017) investigates the role of big data analytics in improving manufacturing processes and reducing machine downtime, speed and quality loss.

Moreover, the concept of OEE has been extensively researched in the manufacturing industry. OEE is a performance metric used to measure the overall effectiveness of equipment by combining three factors: availability, performance, and quality. A study by (Nakajima, 1988) introduced the concept of OEE and highlighted its importance in identifying and measuring losses in manufacturing operations. According to (Chandra, 2018), (Berzins, 2022), (Yuniawan, 2014), (Maran, 2012) the mathematical analysis of OEE is:

$$\text{Availability} = \frac{\text{Run time}}{\text{Planned working time}} \ldots\ldots\ldots 1$$

$$\text{Performan} = \frac{\text{Actual Production Time}}{\text{Planned Production Time}} \ldots\ldots .2$$

$$\text{Quality} = \frac{\text{Total No. of good quantity produce}}{\text{Total No. of total quantity produced}} \ldots\ldots\ldots 3$$

$$\text{OEE} = A * P * Q \ldots\ldots 4$$

When the losses of the auxiliary machines are weighted OEE, the following formulation is used

$$\text{Weighted Availability} = \frac{(A1 * W1) + (A2 * W2) + \ldots + (An * Wn)}{\text{Total weight}} .5$$

$$\text{Weighted Performance} = \frac{(P1 * W1) + (P2 * W2) + \ldots + (Pn * Wn)}{\text{Total weight}} .6$$

$$\text{Weighted Quality} = \frac{(Q1 * W1) + (Q2 * W2) + \ldots + (Qn * Wn)}{\text{Total weight}} .7$$

$$\text{OEE} = \text{weighted averages of the Availability} * \text{weighted averages Performance} * \text{weighted averages Qualit} \ldots .8$$

Overall, the literature suggests that the integration of Industry 4.0 technologies into manufacturing operations can help improve OEE and reduce downtime, speed and quality loss, resulting in increased effectiveness and profitability. The study presented in this paper contributes to the existing literature by providing a practical application of Industry 4.0 approaches in a manufacturing setting and highlighting their effectiveness in enhancing OEE.

Methodology:

The methodology section describes the research design, data collection, and analysis methods used in the study. The research design is an explanatory research design, which establishes a cause-and-effect relationship between the use of Industry 4.0 technologies and the improvement of OEE. The data collection methods include both primary and secondary data sources, including department logbooks, technical apps, smart machines, observations, interviews, and questionnaires with respondents, operators, employers, and technical managers. The data analysis methods include big data analysis, computer algorithms, and predictive solution. The overall step is like

e) Introduction:
- Identifying equipment effectiveness metrics for effective operation of auxiliary grand machines
- Conducting a thorough analysis of current processes and identifying areas for improvement
- Identify the nature of the operation process, focusing on the operation type and process
- Identify the technology and potential practises for productivity losses and equipment operation
- List and grouped the activities and resources needed for the manufacturing operation.

f) Collecting, organizing, and analysing data
- Collection and development of a data type and source

Collecting data from various sources such as production systems, machines, equipment, or technology (sensor, recorder, computer numerical control, display cabinmates, machine learning, and vision), technique and maintenance, supervisory control and data acquisition (SCADA), quality and research development, plant manager, data room, department documents, blue- and white-collar worker interviews, and machine logbooks.

- Data analysis: to identify trends and patterns that can inform decision-making

Analyzing the data using advanced analytics techniques, such as computer algorithm, machine learning with representative chart like (cluster, run and cluster chart). random forest, and pattern recognized trained with data are used to full filed the missing data and to convert the data in recognized pattern respectively. Improving OEE using industry 4.0 (best integrated techniques and practises):
- Industry 4.0 technologies and tools
- BMP-based maintenance planning, and correction
- Big data, from big data handling, missing data (random forest (RF))
- Recognize patterns in data (pattern recognized trained with data)

g) Conclusion
- Benefits of using BMP for OEE analysis and improvement, using industry 4.0
- Encourage employees' participation in problem solving and improvements in industry 4.0
- Future direction of research and recommendation.

Identifying the impact of industry 4.0 technologies, such as automation and connectivity, on operations and identifying areas where these technologies can be further given possible solution and mitigated to improve performance continuously monitoring, evaluating, and adjusting the process to make sure the desired level of OEE is maintained.

h) References

Results and discussion:

The Hilina-enriched food manufacturing industry recognizes and gives credit to all the sources of data related to the manufacturing information listed below. The collected data from the manufacturing process is utilised for analysis and evaluating the overall equipment effectiveness of the manufacturing process. Is relied upon to determine the daily, weekly, and monthly equipment status, and production output, Additionally, contains data on the number of minutes lost and the frequency of breakdowns, change over, idleness, and start-up. The required information is gathered from each of the manufacturing sections in accordance with the manufacturing system process.

The information gathered spans the eight-month period from October 2022 to May 2023, but the data is covered from January 2022 to May 2023. To identify the current manufacturing system, process, recursion factors affecting OEE, and metrics of the manufacturing system, as well as to understand the system fluctuation on the variation bottleneck among the schemes, recursion problems, cutting-edge technology and tools (industry 4.0) on the improvement of OEE, a great deal of big data collected.

From auxiliary grand machine data analysis using the above equations (1 to 8), the current auxiliary OEE trend is shown in table 1.

Table 1 Auxiliary machine OEE

Auxiliary machine	A (in%)	P (in%)	Q (in%)	OEE (in %)
Roaster machine	86.91	95.93	89.70	74.79
Sortex machine	87.41	95.71	95.01	79.49
Pre-Blend machine	86.79	93.62	98.94	80.39
Grinder & Mixer A	86.08	91.67	99.00	78.12
Blend machine	86.10	93.94	98.68	79.81
Grinder & Mixer B	85.75	91.39	98.70	77.35
Vacuum pump	87.42	94.92	99.98	82.96
Thermal treatment	87.88	95.72	99.98	84.10
OEE	86.79	94.11	97.50	79.64

$$\text{OEE auxilary machine} = \text{weighted averages of the Availability} * \text{weighted averages Performance} * \text{weighted averages Qualit} = A * P * Q \ldots\ldots (\text{from equ } 8) = 86.79\% * 94.11\% * 97.50\% = 79.64\%$$

Based on this analysis, it can be concluded that the OEE (Overall Equipment Effectiveness) of the auxiliary machines in the Hilina Enriched Energy Manufacturing Industry is generally quite high, with most machines showing OEE values in the range of 74.79% to 84.10%.

And the filler and packaging machine OEE is like to be

Table 2 Filler and packaging machine OEE

Filler & packaging	A (in %)	P (in %)	Q (in%)	OEE (in %)
A	41.08	46.45	90.10	17.19
B	64.94	55.89	89.38	32.44
C	75.17	62.21	83.98	39.27
D	67.54	35.52	90.53	21.72
E	70.18	60.46	87.98	37.33
F	57.23	60.22	86.53	29.82
G	69.17	59.41	96.27	39.56
H	69.17	59.41	82.68%	33.98
I	72.83%	59.41	96.27	41.65
J	72.83%	59.41	96.27	41.65
OEE	66.60	55.83	90.00	33.46

$$\text{OEE filler \& packaging} = \text{weighted averages of the Availability} * \text{weighted averages Performance} * \text{weighted averages Quality} = A * P * Q \ldots\ldots (\text{from equ } 8) = 66.60\% * 55.83\% * 90.00\% = 33.46\%$$

Based on the data provided, it seems like the Hilina Enriched Food Manufacturing Industry has room for improvement in terms of overall equipment effectiveness (OEE) for the filler and packaging machine category, as the OEE of the overall machines is only 33.46%. Upon further analysis, it can be seen that the performance of the machines is particularly low, with several machines showing percentages below 60%, which can significantly contribute to a low OEE. Therefore, the manufacturing industry needs to investigate the root causes of the low performance and take the necessary steps to address them in order to improve the OEE as a whole. It is also noteworthy that some machines have a relatively lower quality percentage, which affects the overall OEE of the machines. Improving the quality percentage of the machines can further help enhance the equipment effectiveness of the factory. proposes possible solutions for enhancing OEE through the use of Industry 4.0 technologies, such as real-time monitoring, data analytics, automation, and predictive maintenance.

Therefore, the study's findings suggest that Industry 4.0 technologies can significantly improve OEE in manufacturing companies by giving a possible solution on recursion problem on auxiliary grand machine, especially on filler and packaging machine, since these problems are the major reason for largest downtime, speed and quality losses of the auxiliary grand machines.

After propose solution for such recursion problems: dose, horizontal leakage, vertical leakage, horizontal seal, vertical seal, man power, nitrogen, printer, eye mark, thermal, knife, alignment, mix delay, sachet unwinding, with its possible solution like: predictive maintenance: technology and tools, such as machine learning algorithms, are utilized to anticipate when maintenance work on equipment is necessary before it breaks down and speed and quality losses occur, downtime decreased or speed and quality increased; consequently, OEE will be raised by identifying and resolving potential problems before they become serious ones, monitoring in real time: Industry 4.0 technologies and tools offer real-time monitoring of equipment status and operation. Because of this, operators respond to problems as they develop more rapidly, cutting downtime, speed, and quality loss, which then raises OEE, and data analytics is industry 4.0 technology used to examine data from manufacturing processes, find trends, and gain insights that can be applied to improve output and cut down on downtime and speed losses. Automation: technology like robotics and automation helps lower manual lab or and mistakes, enhancing effectiveness and lowering downtime, speed, and quality losses. These possible solutions the estimated improvement of OEE in Hilina manufacturing industry. By using predictive maintenance and real-time monitoring algorithms and installing sensors to monitor oil levels, detect vertical and horizontal leaks, seal, jaw and clutch cracking in real-time, maintenance activities can be scheduled proactively, reducing unplanned downtime, speed and quality losses and increasing OEE. This study conducted company has shown that predictive maintenance can reduce maintenance costs by up to 30% and improve equipment availability, performance and quality by 20% (Kinsey, 2018), (McRoberts, 2018), (Bashir, 2022). Therefore, due to this the possibility solution is changed the current or existence parameters to estimated possibility solution, are presented in table 3 and 4 below.

Table 3 Overall current result of the auxiliary grand machine

Auxiliary machine	A (in%)	P (in%)	Q (in%)	OEE (in %)
Auxiliary machine	86.79	94.11	95.50	79.64
Filler and packaging	66.60	55.83	90.00	33.46
Auxiliary grand	82.62	86.21	95.95	68.34
OEE	68.34%			

Overall, for this analysis, the OEE for Hilina's manufacturing factory is 68.34%, which means that the factory is using 68.34% of its manufacturing time effectively. This is a low score compared to the ideal OEE of world-class, which indicates that there are many losses and inefficiencies in the manufacturing process. The analysis also shows that the auxiliary machines have a higher OEE than the filler and packaging machines, which means that the latter machines need more improvement in terms of availability, performance, and quality.

After providing possible solution

Table 4 Overall estimated improved OEE of the auxiliary grand machine

Auxiliary machine	A (in%)	P (in%)	Q (in%)	OEE (in %)
Auxiliary machine	87.29	94.61	98.00	80.93
Filler and packaging	76.01	65.84	95.00	47.84
Auxiliary grand	84.96	88.67	97.38	73.36
OEE	73.36%			

Conclusion:

This study under taken on the improvement of system metrics; and the analysis were done started from, auxiliary grand machine especially filler and packaging machine, data analysis, and findings related to the improvement of OEE using Industry 4.0. The answer goes into detail about how Industry 4.0 technologies, such as big data analytics and machine learning algorisms, are used to improve OEE performance through data analysis and decision-making. The three OEE drivers of availability, performance, and quality are used to identify the core causes of OEE loss in order to improve OEE performance.

Make data-driven decisions that can improve OEE performance with Industry 4.0 technologies like big data analytics, smart device, machine learning and vision, and the Internet of things. Finally, the improvement estimation Hilina energy-enriched food manufacturing company, diagram was developed in comprehensive way and according to the proposed the OEE system using Industry 4.0 slightly increased to 68.34 percent up to 73.36 percent through a possible solution for observed problems.

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Appendix II: Sample data in Hilina Energy Enriched food manufacturing industry

Appendix A Quality and production

Months	Plan	Nut	Sup	No of mix Nut	No of mix Sup	Sachet loss (meter)	Product loss (Kg)	Total product (Ton)	Sachet loss nut (Meter)	Sachet loss sup (Meter)	Product loss nut(kg)	Product loss sup(kg)	Total product loss
Jan	700	130.17	341.28	101	264	9081	983	471.45	2685.47	6395.85	197.8	785.29	983.09
Feb	700	476.03	10.2	369	8	16676.16	1372.27	486.23	16422.16	254.04	1343.7	28.5	1372.2
Mar	700	662.66	55.59	513	43	15927.9	1490.78	718.25	14189.85	1735.05	1299.98	190.08	1490.06
Apr	700	661.31	0	512	0	16235.86	1571.95	661.31	16235.9	0	1571.95	0	1571.95
May	700	257.47	192.76	199	149	11548.43	1065.89	450.23	6696.68	4851.75	678.26	387.63	1065.89
June	700	240.36	500.47	186	386	17841.57	1457.92	740.83	5477.6	12363.7	495.1	962.67	1457.77
July	700	541.47	67.17	419	52	13605.31	995.11	608.64	11562.19	2043.15	815.59	179.52	995.11
Aug	700	616.83	0	478	0	17385.94	1385.26	616.83	17385.9	0	1385.26	0	1385.26
Sep	700	3.96	0	3	0	92.66	18.38	3.96	92.66	0	18.38	0	18.38
Oct	700	420.37	177	326	137	16768	1302.03	597.37	11329	5439	824.91	477.12	1302.03
Nov	700	239.89	454.83	186	352	26923.5	1762.89	694.72	8770.55	18152.9	580.47	1182.42	1762.89
Dec	700	496.86	144.43	385	112	16669.6	1278.06	641.29	12459.9	4209.7	964.55	313.51	1278.06
Total tone	8400	4747.38	1943.73	3677	1503	178755.9	14683.5	6691.11	123307.86	55445.14	10175.95	4506.74	

Appendix B Raw material

Months	Type of peanut	Unit	Raw sorted peanut	Infested peanut	Hull	Loss due to moisture	Roaster loss	Sortex loss	Total Loss on roaster + Sortex	Loss %	Remaining Roasted-Sorted peanut
Jan	Local Peanut without shell	kg	0	0	0	0	0	0	0	0%	0
	Imported peanut without shell	kg	162500	11068	6062	15186	21248	11068	32316	20%	130184
	Total sorted peanut		162500	11068	6062	15186	21248	11068	32316	20%	130184
Feb	Local Peanut without shell	kg	2777	201	98	218	316	201	517	19%	2263
	Imported peanut without shell	kg	125000	5547	4813	7662	12475	5547	18022	14%	106978
	Total sorted peanut		127777	5748	4911	7880	12791	5748	18539	15%	109241
Dec	Local Peanut without shell	kg	0	0	0	0	0	0	0	0%	0
	Imported peanut without shell	kg	175000	7773	6419	13399	19818	7773	27591	16%	147409
	Total sorted peanut		175000	7773	6419	13399	19818	7773	27591	16%	147409
Total imported peanut		kg	2,075,000.00	92,716.00	73,796.00	139,804.00	213,600.00	92716	306316	15%	1,617,976.00
		Tone	2075	92.716	73.796	139.804	213.6	92.716	306.316	15%	1617.976
Local Peanut without shell		kg	2777	201	98	218	316	201	517	19%	2263
Local + imported		kg	2,077,777.00	92,917.00	73,894.00	140,022.00	213,916.00	92,917.00	306,833.00	0.33	1,620,239.00

Appendix C Availability

Week	Total downtime								Planned downtimes								Unplanned downtimes								Total working time in min	Total planned downtime in min.	Total planned working time in min.	Total unplanned downtimes in min.
	A	B	C	D	E	F	GH	IJ	A	B	C	D	E	F	GH	IJ	A	B	C	D	E	F	GH	IJ				
week 1 to 22	6101	10080	6475	5475	5065	5075	11314	0	3945	3300	3980	4070	3850	3820	7640	0	2156	6780	2495	1405	1215	1255	3674	0	80640	30605	50035	18980
	2733	9660	3970	5030	4251	5942	4960	0	1196	165	1076	2806	2336	2417	2948	0	1537	9495	2894	2224	1915	3525	2012	0	80640	12944	67696	23602
22	9540	6585	6330	9470	9540	9540	19080	16080	7740	5275	5215	6460	7650	4860	9720	13900	1800	1310	1115	3010	1890	4680	9360	2180	100800	60820	39980	25345
total minute	194611	122591	98090	133033	131319	158633	262238	181320	90768	62900	59143	67245	62312	57541	161088	153732	1038443	59691	38947	65788	69007	101092	101150	27588	2116800	714729	1402071	567106
	1281835								714729								567106											

Appendix D performance

Production speed (PCS/min) 2021/2022												
Week	Date	Date		A	B	C	D	E	F	G and H	I and J	Plant Performance
Week 2 to 52	Design Capacity			50	50	50	50	50	50	50	50	400
	Monday	4-Jan	Shift 1	45	45	46	46	47	45			274
			Shift 2	45	45	46	46	45	45	4	4	280
			Shift 3									0
	Tuesday	5-Jan	Shift 1	45	45	46	46	47	46			275
			Shift 2	45	45	46	46	47	46			275
			Shift 3				46	47	45	4	4	146
	Wednesday	6-Jan	Shift 1	45	44	45	44	47	45			270
			Shift 2	44	45	44	44	47	45			269
			Shift 3				44	47	44	4	4	143
50pcs/min	5000gr/min	actual	total	24268	29205	32507	18558.30	31591.00	31463.00	31042.00	31042.00	229676.30
	kg/hr.			145608.0	175230	195042.0	111349.8	189546.0	188778.0	186252.0	186252.0	1378057

	kg/day			2096755	25233120	28086048	16034371	27294624	27184032	26820288	26820288	19844032
	tone/hr.			873.65	1051.38	1170.25	668.10	1137.28	1132.67	1117.51	1117.51	8268.35
	tone/day			125.81	151.40	168.52	96.21	163.77	163.10	160.92	160.92	1190.64
	5000gr/min	design capacity	total	52250.00	52250.00	52250.00	52250.00	52250.00	52250.00	52250.00	52250.0	522500.0
	kg/hr.			313500.0	313500.0	313500.0	313500.0	313500.0	313500.0	313500.0	313500.	2508000.
	kg/day			451440	451440	4514400	4514400	4514400	4514400	4514400	4514400	36115200
	tone/hr.			270864.0	270864.0	270864.0	270864.0	270864.0	270864.0	270864.0	270864.0	2166912.0
	tone/day			39004.42	39004.42	39004.42	39004.42	39004.42	39004.42	39004.42	39004.42	312035.33
	5000gr/min	difference	total	27982.00	23045.00	19743.00	33691.70	20659.00	20787.00	21208.00	21208.00	292823.70
	kg/hr.			167892.0	138270.0	118458.0	202150.2	123954.0	124722.0	127248.0	127248.0	1129942.2
	kg/day			24176448	19910880	17057952	29109628	17849376	17959968	18323712	18323712	162711676
	tone/hr.			269990.3	269812.6	269693.7	270195.9	269726.7	269731.3	269746.4	269746.4	2158643.6
	tone/day			38878.61	38853.02	38835.90	38908.21	38840.65	38841.31	38843.49	38843.49	310844.69

Appendix E downtime

week	Total downtime								Planned downtimes								Unplanned downtimes								Total working time in min	Total planned downtime in min.	Total planned working time in min.	Total unplanned downtimes in min.
	A	B	C	D	E	F	GH	IJ	A	B	C	D	E	F	GH	IJ	A	B	C	D	E	F	GH	IJ				
1	6101	10080	6475	5475	5065	5075	11314	0	3945	3300	3980	4070	3850	3820	7640	0	2156	6780	2495	1405	1215	1255	3674	0	80640	30605	50035	18980
2	2733	9660	3970	5030	4251	5942	4960	0	1196	165	1076	2806	2336	2417	2948	0	1537	9495	2894	2224	1915	3525	2012	0	80640	12944	67696	23602
21	10440	5997	4240	3964	4943	4280	14556	13570	10440	2298	2598	2150	2135	1975	11758	12008	0	3699	1642	1814	2808	2305	2798	1562	100800	45362	55438	16628
22	7200	2475	2071	1782	7159	2033	2946	2188	7200	844	1015	770	1459	1078	1194	1448	0	1631	1056	1012	5700	955	1752	740	100800	15008	85792	12846
total minute	194611	122591	98090	133033	131319	158633	262238	181320	90768	62900	59143	67245	62312	57541	161088	153732	103843	59691	38947	65788	69007	101092	101150	27588	2116800	714729	1402071	567106
	1281835								714729								567106											

Appendix F No of recursion problem

week	Machine	back date	horizontal leakage	vertical leakage	horizontal seal	vertical seal	printer	eye mark	thermal	knife	alignment	mix delay	sachet unwinding	clutch	valve seal	sealing temperature	Kentrol	three-way valve	other	Total Per Week
1	A	0	25	0	0	0	25	0	0	0	0	240	0	1270	0	0	0	0	576	6101
	B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	480	10080
	C	0	32	0	0	0	10	0	0	0	195	45	0	1683	0	0	0	0	530	6475
	D	0	46	0	0	11	0	0	0	10	0	195	0	0	0	0	0	60	603	5475
	E	0	193	0	0	52	0	0	0	55	0	250	0	0	0	0	0	0	630	5065
	F	0	167	0	0	30	0	35	0	0	0	277	0	0	0	0	70	0	641	5075
	GH	0	47	0	0	0	0	0	0	296	21	250	0	0	0	0	0	0	1188	11314
	IJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	B	0	377	854	0	0	50	10	0	31	84	15	0	0	0	0	15	84	235	2475
	C	0	114	693	0	0	86	13	0	4	65	15	0	0	0	0	0	0	253	2071
	D	0	120	424	0	0	127	15	0	0	263	15	0	0	0	0	0	0	208	1782
	E	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5700	7159
	F	0	48	176	0	0	307	0	0	0	15	15	0	0	0	0	46	0	373	2033
	GH	0	0	0	0	0	9	14	0	581	116	15	60	0	0	0	0	0	307	2946
	IJ	0	0	58	0	0	29	93	0	0	106	15	0	0	0	0	0	0	398	2188

Appendix G Recursion problem with downtime

Machine	dose	three-way valve	horizontal leakage	vertical leakage	Nitrogen	printer	eye mark	knife	alignment	sachet unwinding	clutch	sealing temperature	Kentrol	sachet congregates
A	0	0	2	0	0	1	0	0	0	0	3	0	0	0
B	14	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	3	0	0	1	0	0	0	0	6	0	0	0
D	0	1	3	0	0	0	0	1	0	0	0	0	0	0
E	0	0	9	0	0	0	0	2	0	0	0	0	0	0
F	0	0	7	0	0	0	2	0	0	0	0	0	1	0
GH	0	0	4	0	0	0	0	7	1	0	0	0	0	0
IJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	2	3	0	0	0	0	0	0	0	0	0	0
B	27	0	0	0	0	0	0	0	0	0	0	0	0	0
C	5	0	0	1	0	0	0	0	0	0	0	0	0	0
D	0	0	3	0	0	0	0	1	0	0	0	0	0	0
E	2	0	2	0	0	0	0	0	0	0	0	0	0	0
F	0	0	1	0	0	0	0	0	0	0	0	0	2	0
GH	0	0	2	0	0	0	0	0	5	0	0	0	0	0
IJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix III: Enquiring

This survey aims at establishing factors affecting the overall equipment effectiveness (OEE) of Hilina Enriched Food PLC: The survey is designed to collect data that will help achieve the objectives of the study. We kindly request you to participate in this study by responding to all the questions as candidly and precisely as possible. Your honesty and co-operation in responding to the questions will highly be appreciated. All information provided will be treated with the most confidentiality and will be used purely for research purposes.

1) How do you think Industry 4.0 or cutting age technology and tools can improve the identification of potential equipment failures before they occur?

2) How do you think Industry 4.0 or cutting age technology and tools can improve the accuracy and speed of maintenance and repairs?

3) What problems do you often face regarding the availability of machine accessories and maintenance tools (especially when simultaneous maintenances take place)?

4) What are the tools that are usually less in amount resulting hindrance from doing your job?

5) How do the quality and availability of the following raw materials affect the machinery's flawless functioning and the effectiveness of the production?
   - ✓ Mechanical equipment's
   - ✓ Electrical equipment's
   - ✓ Data recorders
   - ✓ Any other raw material

GENERAL

- ✓ During changeovers, and breakdown, after setup takes place what is the reason for the delay in production?

6) What are the main challenges you face in achieving optimal OEE in your production processes?

7) Are there any specific challenges you face when it comes to maximizing effectiveness and output during your workday?

8) How can Industry 4.0 or cutting age technology and tools help to optimize production scheduling and minimize downtime?

9) How can Industry 4.0 or cutting age technology and tools help to streamline communication and collaboration between different departments involved in the manufacturing process?

10)

11) What methods have you used to improve OEE these areas until now?

12) What kind of methods did you use to help your workers hit performance OEE goals and succeed?

13) How do you closely monitor your employees' (operators and chemists) discipline & being on time during production hours?

14) What problems do you often face while supervising?

15) Write your comments on the communication you have with the Operational excellency team?

16) How and when are you informed when you have to make production changeovers?

17) What do you think the problem with late changeovers and production is with respect to communication?

18) What tactics do you implement to control your employees to be OEE focused?

19) What positive effects on OEE have the methods you used in the past had, especially compared to your expectations?

20) How do you currently manage the maintenance process in the manufacturing plant?

21) Have you considered using Industry 4.0 or cutting age technologies and tools to enhance the maintenance process?

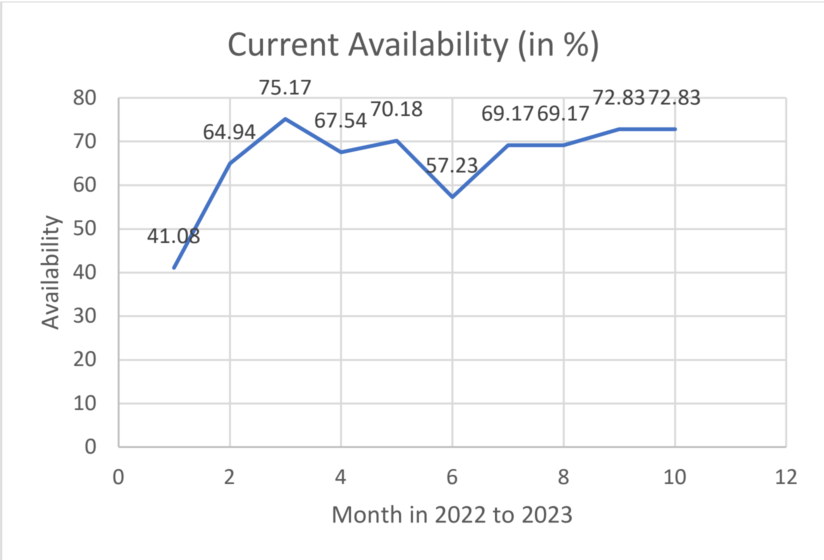
22) How can Industry 4.0 or cutting age technology and tools help to improve the predictive maintenance process?

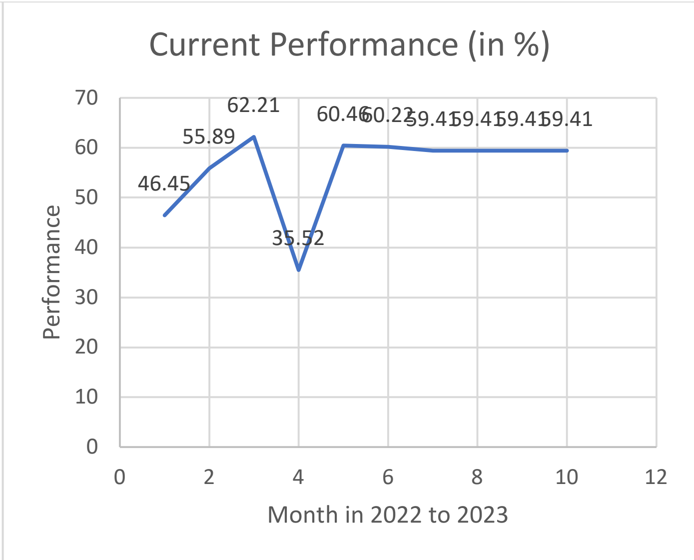
23) How can Industry 4.0 or cutting age technologies and tools help to improve the allocation of maintenance resources and reduce costs?

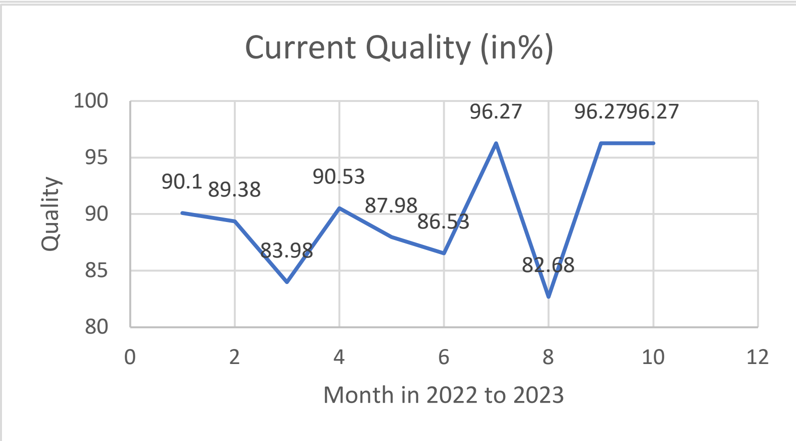
24) What's your stance on the idea that there's a shortage of maintenance tools that are available to your team?

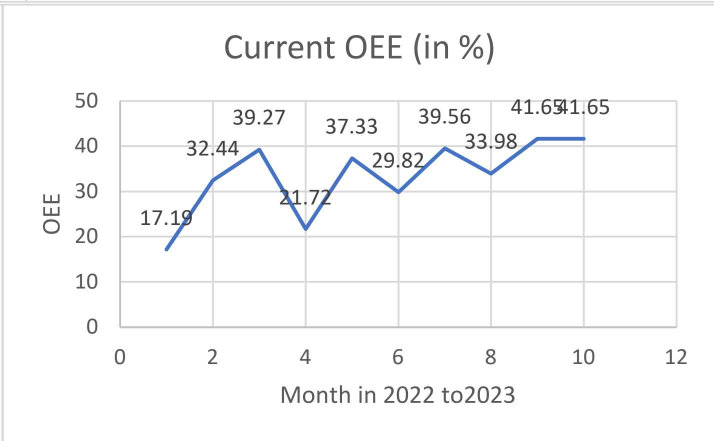
25) If you agree with the fact that there's a shortage of tools, then what do you think is the problem behind it?

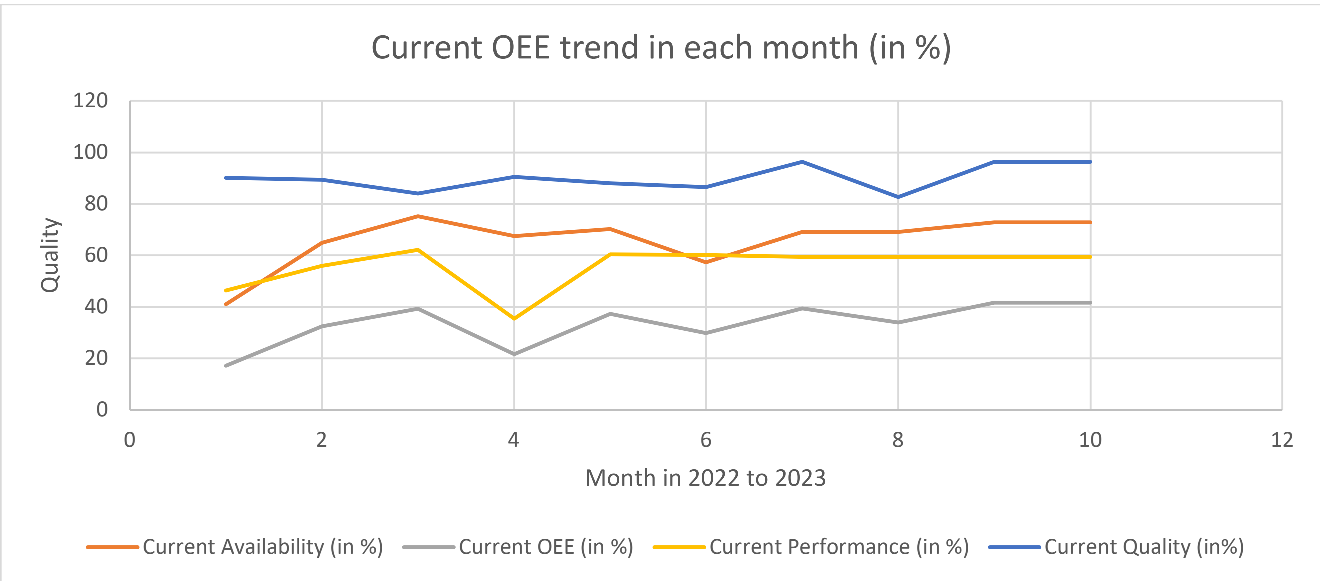
Appendix IV: Current and Expected OEE trend in each month











Expected OEE trend in each month