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An Artificial Intelligence and Reliability Centered Maintenance Based Approach for Improving Machine Effectiveness in the Manufacturing Industry

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Abstract

Most manufacturing companies utilize the overall equipment effectiveness (OEE) metric to monitor performance. Its computation provides managers with the opportunity to identify significant losses resulting from reduced machine effectiveness and make informed decisions to rectify the situation. This paper developed a systematic framework based on the reliability-centered maintenance (RCM) approach and an artificial neural network (ANN) to identify the primary losses and minimize the high downtime of production machines and product defects, thus increasing their OEE. The framework consists of five main implementation phases, which are. System description and critical system selection, critical machine analysis and evaluation, defect assessment, and assessment of idling and stoppage losses. An ANN technique is suggested to assess the hazard degree of the failure modes from critical components, determine maintenance mode decisions, calculate maintenance interval cycles, and perform OEE calculations. The developed framework was applied to the selected real case study as a maintenance and quality controller to minimize the downtime and defect rate. The results demonstrate that Availability and OEE improved from 87% to 97% and 57% to 85%, respectively. Moreover, the results indicate that the applied framework is more accurate and exhibits better performance in predicting overall equipment effectiveness in the selected case study.

Keywords

OEE, reliability-centered maintenance, maintenance system controller, ANN technique, Availability, product quality, system performance.

1. Introduction

In an increasingly competitive global market, driven by increasing demand, firms face ongoing pressure to enhance their production performance (Ahire and Relkar 2012). Achieving high-quality output with minimal downtime and optimal efficiency is a complex and time-consuming task, often accompanied by various operational risks. Failures in the production process can result in significant losses, underscoring the crucial need for a robust performance measurement system that objectively assesses operational efficiency and helps mitigate these risks. One of the most widely adopted metrics for assessing manufacturing performance is Overall Equipment Effectiveness (OEE). OEE offers an in-depth view of the operational efficiency of equipment or entire production systems. By identifying critical loss areas, OEE enables managers to pinpoint inefficiencies and implement targeted enhancement measures, often through optimized maintenance protocols. OEE is determined by three distinct components: Availability, Performance Rate, and Quality Rate (Huang et al. 2003). Availability quantifies the ratio of scheduled production time in which the equipment is functional, factoring in losses from malfunctions, setup durations, and adjustments (Jonsson and Lesshammar 1999). Performance assesses the proximity of the actual operating speed to the optimal speed, accounting for losses due to decreased speed, brief interruptions, and idle (Jonsson and Lesshammar 1999). Quality denotes the proportion of high-quality products relative to the total units manufactured, highlighting losses attributed to defects and rework. In addition, OEE has emerged as a crucial performance metric in modern manufacturing, esteemed for its role in monitoring productivity and quality, as well as directing ongoing improvement efforts. Its systematic methodology enables firms to assess equipment efficiency, prioritize maintenance, and make data-informed decisions that enhance sustainable performance improvements. However, an integrated, advanced method is required to enhance the OEE in production systems.

In recent years, maintenance has undergone a significant transformation in its strategic role within industrial production environments. Initially viewed as a cost center, it has evolved into a critical management function focused on enhancing equipment availability, improving product quality, and increasing overall system efficiency (Jajimoggala, Rao, and Satyanarayana 2011). This evolution has given rise to the field of maintenance engineering, which applies analytical methods and leverages computerized maintenance management systems to plan and execute maintenance activities based on equipment operating conditions. Maintenance involves not only preserving the functional capacity of machinery and equipment but also restoring systems that have failed back to their operational state (Martorell et al. 2005). In industrial plants, effective maintenance and repair activities are essential for ensuring continuous and sustainable production. Inadequate maintenance planning can lead to equipment failures, production losses, and high repair costs due to unplanned downtime. Given the importance and cost associated with maintenance planning, determining the optimal maintenance strategy for machinery and equipment is essential. Implementing inappropriate maintenance strategies can create significant barriers to achieving sustainable production and operational efficiency. The literature presents a wide range of maintenance strategies, including Reliability-Centered Maintenance (Suyog S. Patil et al. 2022; Liu et al. 2023), Condition-Based Maintenance (Garcia et al. 2025), Preventive Maintenance (West et al. 2024), Predictive Maintenance (Garcia et al. 2025), and Corrective Maintenance (West et al. 2024). Selecting the most suitable approach is crucial for minimizing downtime, reducing costs, and ensuring long-term system performance.

Reliability-Centered Maintenance (RCM) is recognized as one of the most effective asset management strategies among various maintenance approaches, with a primary focus on ensuring system reliability. Its main goal is to determine the optimal maintenance plan for system elements while adhering to the facility’s cost constraints. The RCM process consists of three key steps: identifying critical elements for practical inspection, conducting Failure Mode and Effects Analysis (FMEA), and assigning the most suitable maintenance strategy to each failure mode. Among these, identifying critical components is considered the most crucial step, as it directly influences the system's overall reliability. Several studies have demonstrated the effectiveness of the Reliability-Centered Maintenance (RCM) approach in improving maintenance strategies across various industries. For instance, Fore and Msipha 2010 conducted a comprehensive analysis of RCM implementation in a chipping and sawmill company, using the seven standard RCM steps to enhance preventive maintenance (PM) practices. Their work highlighted the structured nature of RCM in identifying and addressing potential failure modes systematically. Similarly, Morad, Pourgol-Mohammad, and Sattarvand 2014 applied the RCM methodology in the Sungun Copper Mine industry to reduce equipment breakdowns and minimize operational downtime. By identifying components with a critical impact on overall equipment availability, they were able to prioritize maintenance decisions effectively, thereby improving system reliability and performance. Suyog Subhash Patil and Bewoor 2022 proposed a comprehensive RCM framework tailored for a steam boiler system in the textile industry. Their study demonstrated the use of a decision logic model to determine the optimal maintenance strategies. The decision-making process, based on failure characteristics, was detailed to assist RCM practitioners in selecting the most suitable maintenance strategies. This structured approach provides practical guidance for implementing effective maintenance planning within similar industrial settings. Hedayatnia et al. 2025 proposed an innovative AI-based method to evaluate the condition of high-voltage circuit breakers (HVCBs) and optimize their maintenance scheduling, with a particular focus on the issue of contact erosion. Maceda-cabrejo, Velazco-gomez, and Meza-ortiz 2025 conducted a study to design and implement a maintenance management model based on RCM aimed at improving operational Availability and reducing losses. Their proposed model integrated FMEA, criticality analysis, and a five-phase RCM strategy. Key components of the model included failure mode identification, task prioritization, and tailored maintenance planning. Following implementation, operational Availability increased from 75.67% to 80%, unplanned stoppages were significantly reduced, and overall maintenance costs decreased.

One qualitative tool for optimizing equipment performance is OEE. Widely used across various industries, OEE serves as a key method for evaluating operational efficiency. It helps identify different types of production losses and pinpoint areas requiring improvement, enabling organizations to implement targeted corrective actions that reduce these losses. Fekri Sari and Avakh Darestani 2019 proposed methodologies to address certain limitations of the OEE and OLE approaches by incorporating intelligent system techniques such as Fuzzy Inference Systems (FIS) and Artificial Neural Networks (ANNs). Their approach provides a more effective means of evaluating OEE and OLE by accounting for varying weights of equipment losses and differences in machine importance. Nurprihatin, Angely, and Tannady 2019 attempted to maintain effectiveness and eliminate losses by calculating the Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR). Niekurzak and Lewicki 2025 outline possibilities and recommendations for enhancing production efficiency without incurring additional costs. ALMashaqbeh (ALMashaqbeh and Hernandez 2024) evaluates the Availability, performance, and quality of a plastic production system in Jordan by integrating the DMAIC and fishbone diagrams, and calculates the OEE measure. Several researchers have used traditional methods to measure the performance of production systems using OEE, but there is limited work integrating RCM with artificial intelligence to enhance the OEE. Therefore, this research will incorporate RCM with ANN to increase the performance of the manufacturing system.

This work aims to develop a framework based on reliability-centered maintenance and artificial intelligence-based ANN to maintenance control and enhance the OEE in the manufacturing industry by reducing or eliminating product failures and losses. To achieve this objective, the problem in the selected manufacturing process was first defined. Second, the framework-based RCM and ANN were developed. Third, the developed framework was implemented to help select a case study that enhances the OEE. Fourth, a maintenance control plan and quality control plan were designed to minimize downtime, defects, and losses. Finally, the results were discussed, and the improvements in the selected manufacturing process were highlighted.

2. Problem definition

The selected company operates 13 production lines, each equipped with its own specialized production equipment. Numerous departments are tasked with maintaining the efficient operation of these 13 pieces of equipment throughout the production lines. This academic analysis will examine three essential operational machines in the service department: the vacuum pump, centrifugal blower, and annealing furnace (Lehr), which are vital for sustaining the airflow and cooling processes necessary for the efficient functioning of the production machine. The failure of any of these three pieces of equipment directly impacts X bottle manufacture, resulting in unusable and defective products. Over the course of two years, the production line experienced substantial output losses due to recurring and prolonged downtimes of these three machines. The vacuum pump incurred more than 500 hours of downtime, the centrifugal blower 753 hours, and the annealing furnace over 800 hours, resulting in a cumulative total of 2,153 hours of downtime. The factory operates continuously, resulting in downtimes that constitute 12.4% of the actual working time over the two years, significantly impacting productivity (as depicted in Figure 1, which presents monthly machine downtimes in hours, and Figure 2, which illustrates the percentage of downtime). The firm experienced a loss of more than 6,000 tons of X bottles from its total production capacity of 39,979 tons, resulting in a 15.2% reduction in production. Figure 3 delineates the monthly output losses. The primary reasons for these downtimes are inefficiencies in maintenance processes, including repair delays and insufficient spare parts, which result in prolonged equipment outages and diminished output. Consequently, it is imperative to devise strategies that improve total equipment effectiveness by minimizing downtime, reducing faults, and enhancing performance. This will be accomplished by developing a systematic approach based on RCM and ANN methods to systematically assess, prioritize, and rectify failures, resulting in a thorough enhancement of Overall Equipment Effectiveness (OEE).

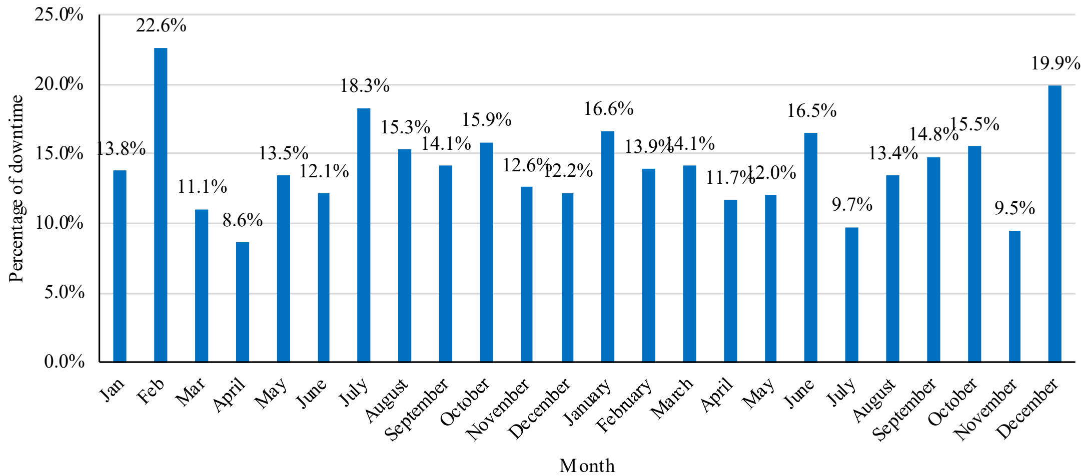

Figure 1. Percentage of downtime

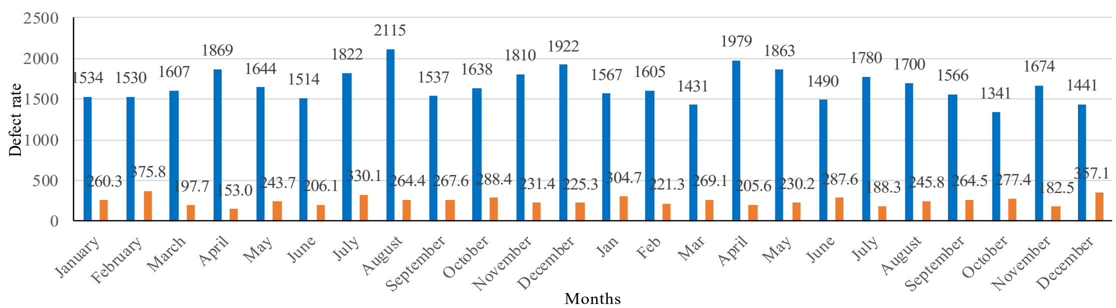

Figure 2. Defect rate

3. Methodology

The objective of this study was to improve OEE performance in the manufacturing process. Figure 3 depicts the proposed RCM framework integrated with an ANN.

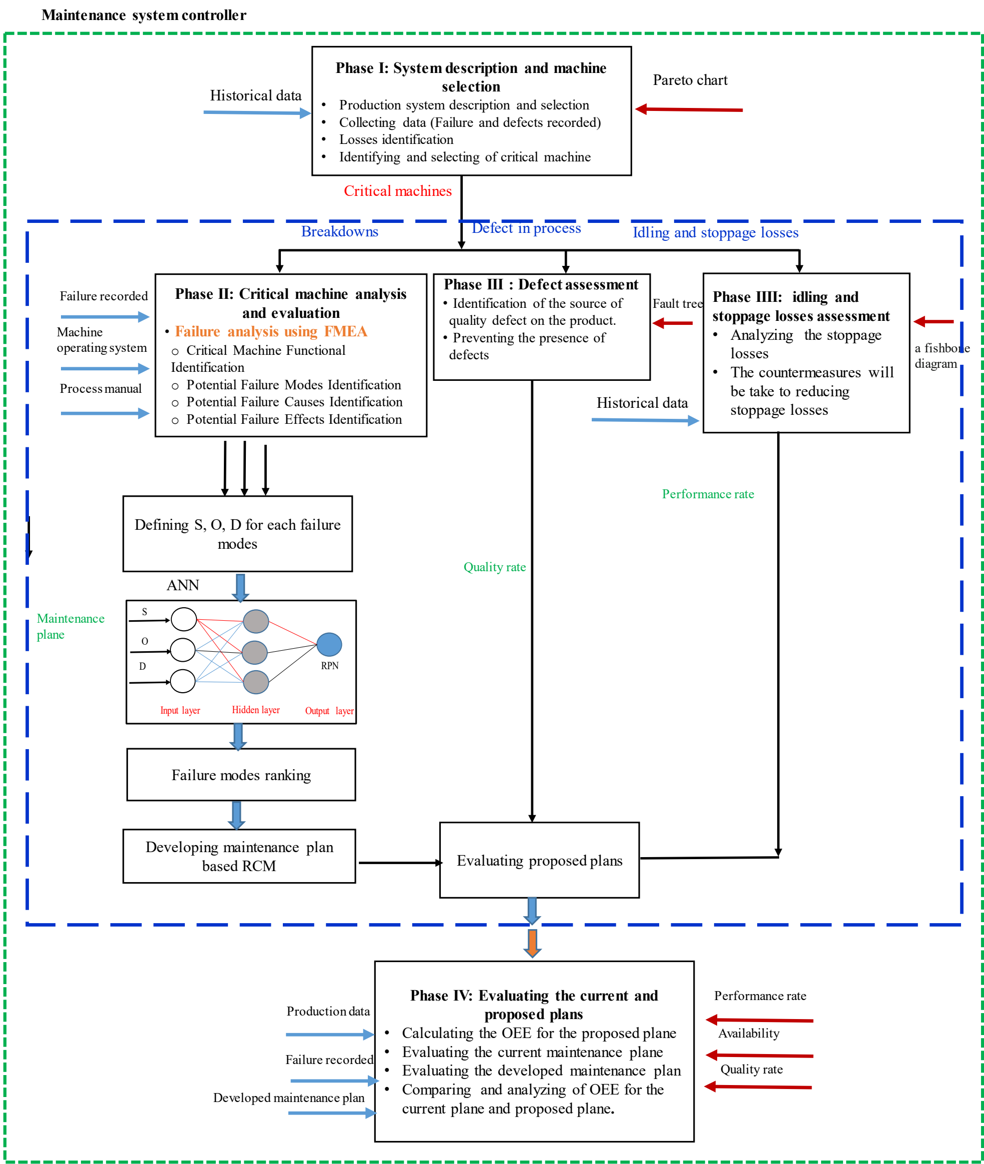

Figure 3. Developed an RCM and ANN framework for controlling the production system

The framework is organized into five main phases to facilitate an efficient implementation process. The first phase involves describing the system and selecting critical systems, focusing on identifying the most essential machines or subsystems based on their impact on overall performance. The second phase focuses on defect evaluation, identifying and assessing flaws that could lead to equipment deterioration or malfunction. In this phase, an ANN technique is also applied to evaluate the danger level linked to critical failure modes in essential components. The third phase focuses on defect evaluation, identifying and assessing flaws that could lead to equipment deterioration or malfunction. The fourth phase focuses on determining losses resulting from idle and unanticipated interruptions, with the objective of identifying their underlying causes and the impact on output. Finally, the fifth phase involves developing maintenance plan decisions, determining the maintenance interval, and calculating OEE after the proposed plans. This structured framework ensures a comprehensive evaluation of system performance and supports data-driven maintenance planning.

3.1 Phase I System description and machine selection

This phase aims to determine the optimal strategies for improving maintenance practices. In a production line comprising multiple machines, a critical system refers to a key component or set of machines whose improved maintenance can significantly reduce downtime, increase the time between failures, and decrease defects and losses. Consequently, overall operational performance measures, including production line availability, will be enhanced, resulting in heightened productivity. The process of making glass bottles involves several key stages: Batch Preparation, Furnace Operations, Forming, Quality Control, and Packaging, as shown in Figure 4. Each stage plays a crucial role in transforming raw materials into high-quality glass containers. All the data provided in this study is supplied by X company.

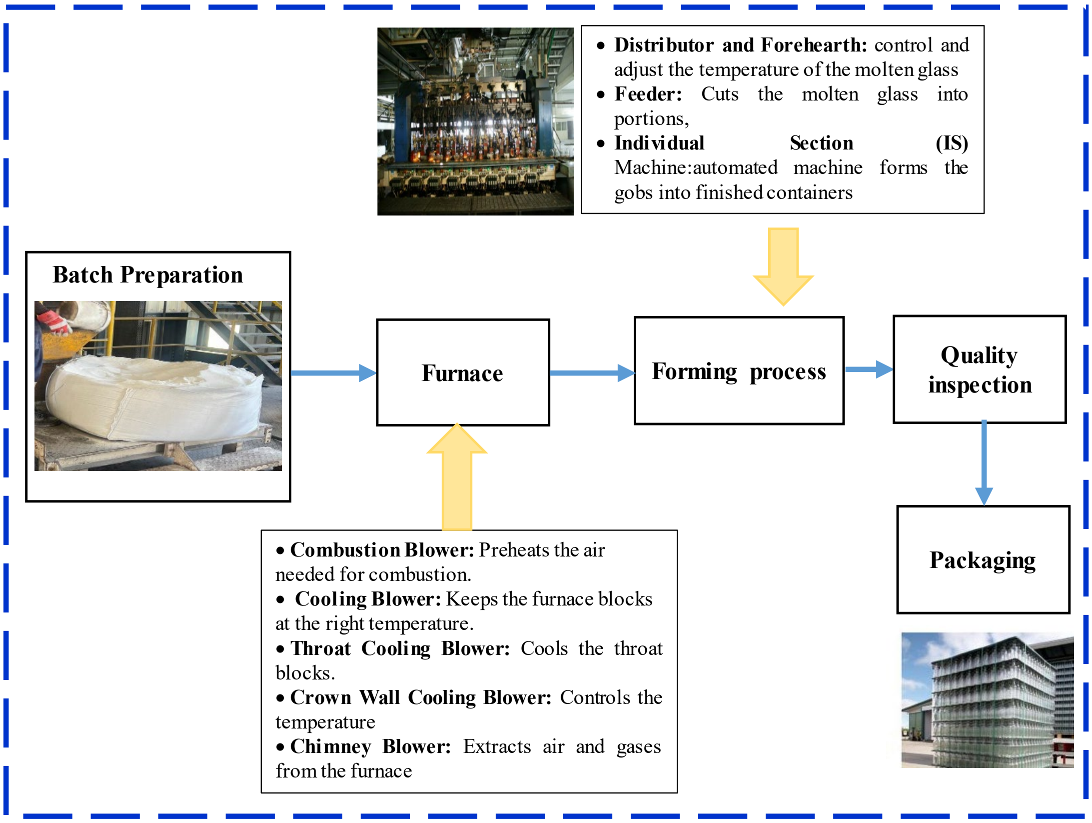

Figure 4. Production systems and their main components

Losses were identified according to the six major categories that affect the efficiency of the production system. These losses were determined through a comprehensive examination of maintenance records and fault reports. As previously emphasized, OEE is affected by six primary categories of losses: breakdowns, setup and adjustments, slowdowns and brief stops, low speed, process flaws, and yield loss. The "six significant losses" impacting machine efficiency are summarized in Table 1.

Table 1. Six big losses

Losses	**Definition**
Breakdown	Losses due to major failures
Setup and adjustment	is used to describe how long it takes to set up or modify equipment so that it is ready for use.
Idling and minor stoppages	Equipment stops working at full production capacity for brief periods, usually due to minor issues or temporary malfunctions.
Reduced speed	Speed losses refer to productivity reductions caused by the machine running below its designed operating speed."

Process defect	Losses due to defects and reworking of products
Startup	Losses due to products that do not accord with specifications at process startup

The critical machine was selected based on the frequency of stoppages and production losses. By using a Pareto chart, as shown in Figure 5, it is possible to identify the equipment with the most significant impact on efficiency and prioritize it for improvement. This allows us to focus on the critical areas that yield the most tremendous benefits.

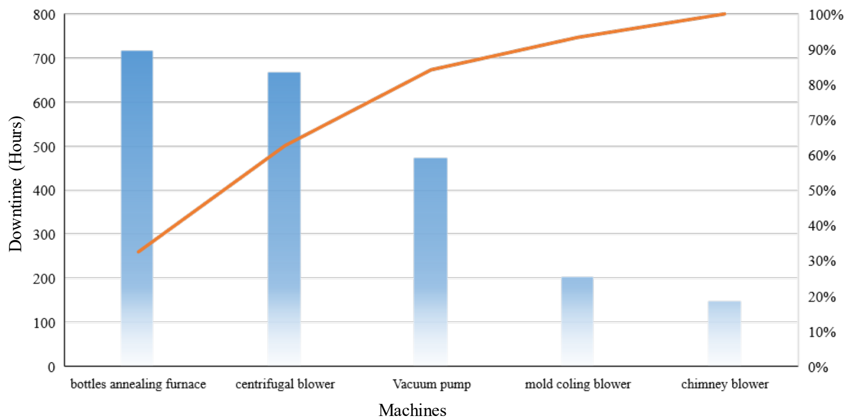

Figure 5. Total downtime for each machine in the production line

According to the Pareto chart, the critical machines with the highest contribution to stoppages and production losses over the past two years are the Bottles Annealing Furnace, Centrifugal Blower, and Vacuum Pump, resulting in a total production loss of 6077 tons of defective bottles. Critical machines will be analyzed in the next section.

3.2 Phase II Critical Machine Analysis and Evaluation

This stage provides deeper technical insights into the critical system, guiding the team in developing a more effective maintenance strategy (see Table 2- Table 4)**.**

Table 2. Main Bottles annealing furnace components

Component	**Failure mechanism**	**Function**
Heating System	Converts electrical energy into thermal energy.	Provides controlled heating to relieve stress in glass products, ensuring product quality.
Drive Motor	Converts electrical energy into mechanical motion.	Powers the conveyor for stable glass movement.
Exhaust Fans	Create negative pressure to remove hot air and fumes.	Maintain stable operation by preventing overheating.
Lehr Mat	Distributes heat and provides a stable surface.	Provides insulation and support for glass.
Conveyor Rollers	Convert rotational motion into linear motion.	Facilitate smooth glass movement through the lehr.
Roller Bearings	Support rotating shafts by reducing friction.	Ensure long-term durability and alignment.
Drive Motor	Converts electrical energy into mechanical motion.	Powers the conveyor for stable glass movement.

Table 3. Centrifugal Blower Components

Component	Failure mechanism	Function
Impeller	Rotates at high speed, creating centrifugal force that causes the fluid to move outward.	Generates fluid movement and increases pressure.
Motor	Converts electrical energy into mechanical energy.	Provides the driving force for the pump, ensuring continuous fluid flow.
Bearings	Support the rotating shaft to reduce friction.	Minimizes wear and enhances pump longevity.
Belt Drive System	Transfers power from the motor to the pump shaft using friction and tension.	Ensures efficient power transfer and prevents slippage.
Shaft	Transmits torque from the motor to the impeller.	Provides a mechanical connection and ensures consistent power transfer.

Table 4. Vacuum Pump components

Component	Failure mechanism	Function
Motor	Converts electrical energy into mechanical energy.	Drives the pump's components and ensures continuous airflow.
Bearings	Reduce friction and support rotational motion.	Support rotating components, reducing wear, and ensuring efficient operation.
Rotor	Generates airflow within the vacuum pump by creating pressure differences.	Creates the vacuum effect by generating controlled airflow and pressure differences.
Belt Drive System	Transfers power from the motor to the rotor or impeller.	Ensures consistent operation by transferring mechanical power.
Cooling System	Dissipates the heat generated by the pump's operation.	Regulates the pump's temperature to prevent overheating.

Identify Failure Mode, Cause, and Effect

After identifying the system's functions and potential functional failures, the next step in the Reliability-Centered Maintenance (RCM) process involves a more detailed and specific analysis. Failure Modes and Effects Analysis is used. Each piece of equipment is selected for detailed evaluation in this step. For each functional location, the organization's past failure data determines failure modes. The study determines the root causes and effects of each failure mode. These effects are measured locally (component impact) and systemically (operational impact). This approach is applied to all equipment items and their associated failure modes to ensure comprehensive system-wide coverage and awareness of risks and implications (see Table 5- Table 7).

Table 5. Identify Failure Mode for the bottles annealing furnace

Failure Mode	Failure Effect	Failure Causes
Damaged Heater	Bad annealing	Overheating
Drive Motor Damaged	Bad annealing / Lehr Stopped	Overloading
Exhaust Fan Damage	Bad annealing	Motor failure
Lehr Matt Damaged	Bad annealing	Wear and tear
Lehr Speed Unstable (FAST)	Bad annealing	Speed sensor malfunction
RC Fan Damage	Bad annealing	Dust accumulation
Roller Bearing Damaged	Bad annealing / Lehr Stopped	Insufficient lubrication

Table 6. Identify the failure Mode for the centrifugal blower

Failure Mode	**Failure Effect**	**Failure Causes**
Belt Cut / Belt loose	Heat accumulation / Bearing Damaged	Overheating
High Vibration / Acceleration	Heat accumulation / Bearing Damaged	Insufficient lubrication
Motor Bearing damage	Heat accumulation / Bearing Damaged	Overheating
Plumber Block Bearing Damaged	Blower stopped	Insufficient lubrication

Table 7. Identify Failure Mode for the Vacuum Pump

Failure Mode	**Failure Effect**	**Failure Causes**
Belt Cut / Belt loose	Stopped / Abnormal sound	Overloading beyond
Low water supply	Pressure is low	Pump malfunction
Motor Bearing damage	Motor Stopped	Lack of Lubrication
Rotor chipping (damaged)	High current / Low pressure	Overheating due to poor cooling or lubrication

- **Development of ANN Prediction Models of Critical Index Calculation (RPN)**

Numerous techniques are available for computing RPN (Ahmad et al. 2012). A conventional variant of RPN computation relies on the parameters of detection (D), occurrence (O), and severity (S). The severity of a failure denotes the impact of a specific failure mode. Occurrence denotes the frequency of a failure mode, while detection signifies the probability of identifying a failure mode. RPN was calculated by evaluating three factors:

$$RPN = S \times O \times D \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

To construct ANN prediction models for the RPN of failure modes, initially define RPN utilizing the S, O, and D components. Subsequently, collect failure mode data and train the artificial neural network (ANN) to predict a more precise, potentially RPN by discerning intricate correlations among Severity (S), Occurrence (O), and Detection (D), thus surmounting the constraints of conventional multiplicative RPN approaches (Chang, Fang, and Li 2025). A neural network typically consists of a multilayer perceptron (MLP), where data passes through several layers of neurons, comprising input layers, hidden layers, and an output layer. The concealed layers comprise several neurons that analyze the input data before transmitting it to the next layer. The network's training function utilizes the Levenberg–Marquardt (LM) method because of its stability and rapid convergence. This algorithm yields numerical solutions by minimizing nonlinear functions. Table 8 shows a sample of ANN prediction models for RPN (Figure 6).

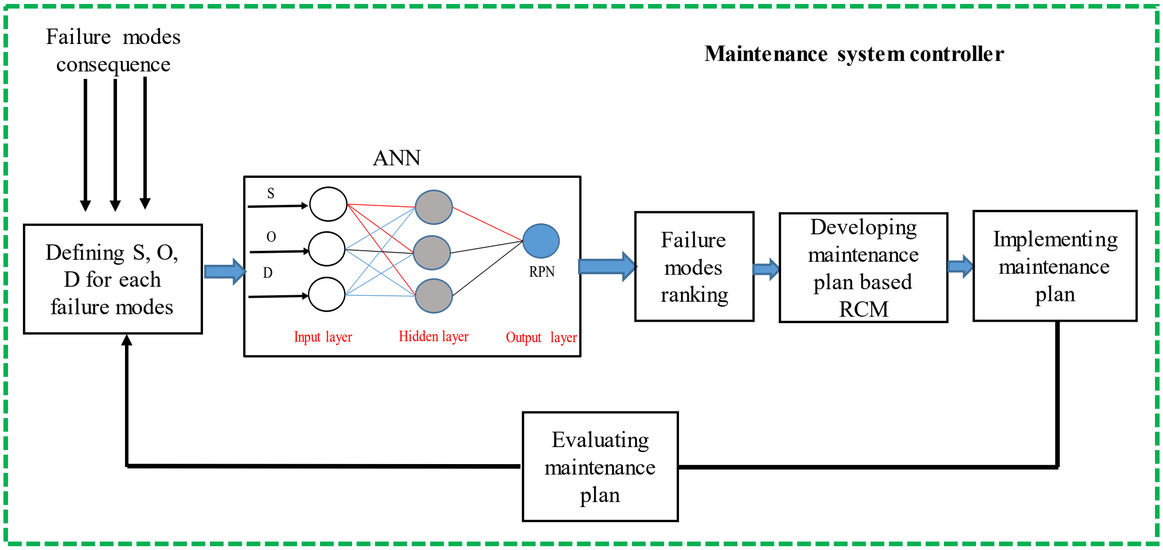

Figure 6. Maintenance system controller based on a neural network model and RCM

Table 8. Calculation (RPN) for the Vacuum pump

Failure Mode	Failure Count	Severity (S)	Occurrence (O)	Detection (D)	Predicted RPN	Rank
Lehr Matt Damaged	18	10	9	6	540	1
Drive Motor Damaged	14	10	8	5	400	2
Damaged Heater	26	9	9	4	324	3
Exhaust Fan Damage	22	8	8	4	256	4
Lehr Speed Unstable	15	7	7	4	196	5
RC Fan Damage	19	6	6	4	144	6

- **Proposed maintenance plan**

After ranking the failure modes for each critical machine, MTBF, MTTR, and DT were collected for each failure mode. Then, a fit distribution was performed to obtain the maintenance interval, and the number of expected failures for two years was calculated to find the required number of parts to minimize the DT. Table 9 shows a sample of a fit distribution.

Table 9. Sample of the Fit distribution

Machine	Failure Mode	Distribution	Expected MTBF (day)	Expected number of Failures
Bottles Annealing Furnace	Damaged Heater	4.5 + WEIB(21.2, 1.14)	24.3	15
Bottles Annealing Furnace	Drive Motor Damaged	0.5 + WEIB(52.9, 1.3)	45.6	8
Bottles Annealing Furnace	Exhaust Fan Damage	NORM(31.9, 27.4)	33.2	11
Vacuum Pump	Rotor Chipping (Damaged)	9.5 + WEIB(11.9, 0.682)	24.3	15

After that, EOQ, Safety Stock, and OP for spare parts were calculated to minimize the time for supplying the parts. All quantity for each failure mode was calculated for two years.

3.3 Phase III: Defect assessment

- **Identification of the source of quality defect in the product.**

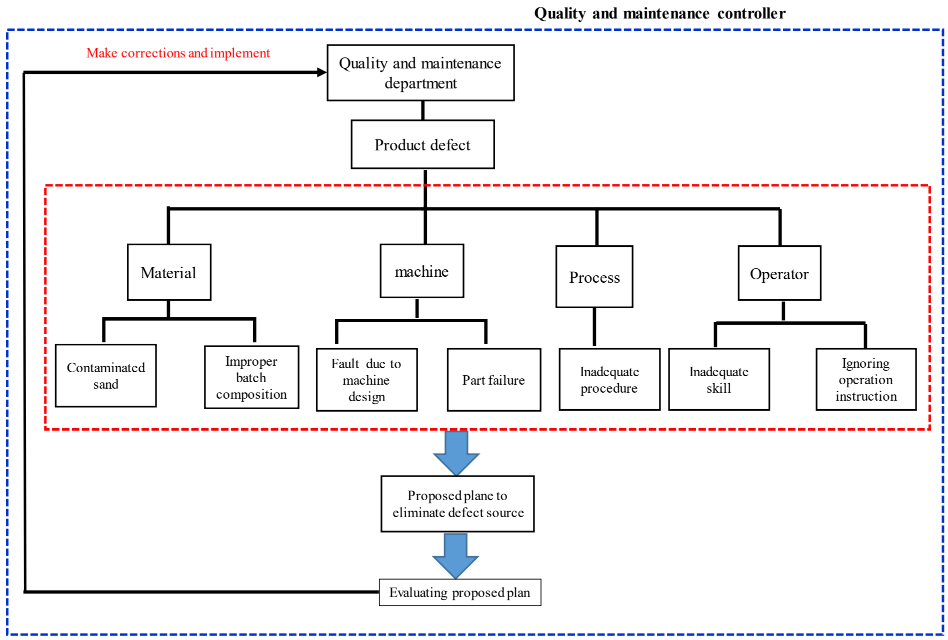

Figure 7. Quality controller for defining, eliminating, and monitoring the source of defects

To identify the sources of defects, a quality controller was developed to define, eliminate, and monitor these sources, as shown in Figure 7. This controller helps estimate the probabilities and frequencies of variables that cause defects, enabling us to identify their root causes. By structuring the developed framework, we can determine the overall likelihood of producing defective products and pinpoint specific areas responsible for these defects. By identifying and categorizing these causes, we can systematically address the underlying issues impacting quality, as shown in Figure 8.

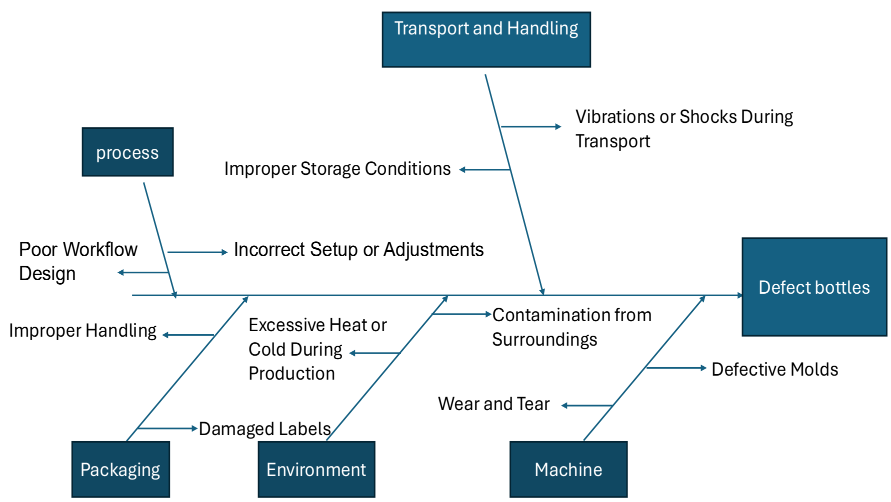

Figure 8. Defect bottles cause and effect

- **Proposed plan for preventing the source of defects**

To reduce defects, we will combine continuous improvement with Preventive maintenance. The Kaizen principle encourages operators to identify and address deficiencies, promoting accountability and ongoing quality enhancement. Preventive maintenance ensures regular inspections and timely repairs, minimizing machine-related faults. Additionally, FMEA will identify and prioritize critical failure modes, enabling targeted actions to improve the quality rate. Figure 9 shows the quality rate for the last two years, indicating that high defect rates can be observed due to a lack of improvements.

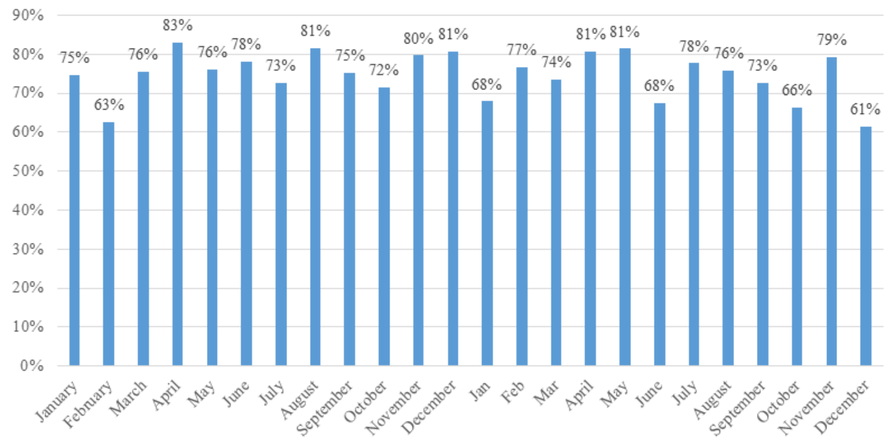

Figure 9. Quality rate for the current system per Month

3.4 Phase IV: Idling and stoppage losses assessment

In this phase, idling and stoppage losses are addressed to improve the performance of the production system. By identifying the root causes of these losses and implementing targeted countermeasures, we aim to enhance operational efficiency and ensure smooth production flow. This phase focuses on analyzing losses and applying corrective actions to minimize their impact on the system's performance.

- **Identification of Stoppage Losses**

To identify the sources of idling time and stoppage losses, a Cause-and-Effect Diagram is used to summarize the losses, as shown in Figure 10. This method systematically analyzes the contributing factors, helping us focus on the root causes. By understanding these causes, we can prioritize actions that reduce unnecessary downtime and improve system performance.

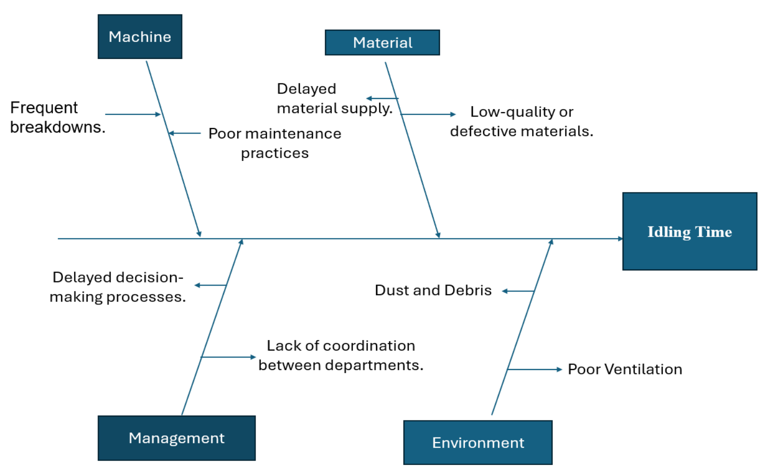

Figure 10. Idling time cause and effect

3.5 Phase V: Evaluating the current and proposed plans

In this phase, the primary goal is to assess the effectiveness of the implemented improvements by comparing the Overall Equipment Effectiveness (OEE) of the current system with that of the proposed plans. This analysis provides a quantitative measure of the success of the interventions and identifies areas for further optimization. The steps involved in this phase include:

- **Calculating the OEE**

To establish a baseline for performance evaluation, the current OEE of the selected machines will be calculated. OEE is determined by analysing three critical factors: Availability, Performance, and Quality Rate. The calculation involves the following steps: Required data for calculating OEE

- Gather historical data from the selected machines on the following parameters:
    1. Required Availability: Total available time for machine operation.
    2. Downtime: Total time the machine was not operational due to breakdowns or maintenance.
    3. Theoretical Cycle Time: The time it takes to produce one unit under ideal conditions.
    4. Units Output: The total number of units produced during the actual operating time.
    5. Actual cycle Time: The total time the machine was running, excluding downtime.
    6. Quality Defect: Total number of defective units produced.
    7. Production output: The total number of units manufactured, including both good and defective ones.

OEE Component Calculations:

Availability (A) = (Required availability − Downtime / Required availability) * 100 ………………………………(2)

Performance (P) = (Units produced in the total shift time / Number of expected units to be produced) *100 ……....(3)

Quality rate (QR) =(Production output−Quality defect / Production output) * 100 …………………………..…………(4)

Overall Equipment Effectiveness (OEE) Calculation

- Combine the three components to calculate the current OEE:
  OEE= A × P × QR …………………………..…………………………………………………………(5)

4. Results and Discussion

Proposed plan for enhancing the Availability, performance, and quality rate

- **Developing a maintenance plan for increasing the Availability based on the maintenance plan**

To reduce downtime and improve equipment reliability. Preventive Maintenance Intervals were developed based on MTBF and the number of Failures for each critical machine: a combined maintenance interval plan for all critical failure modes in all machines. After calculating the expected MTBF and the expected number of failures, Figure 11 shows the interval for replacing damaged parts. This plan decreased the downtime.

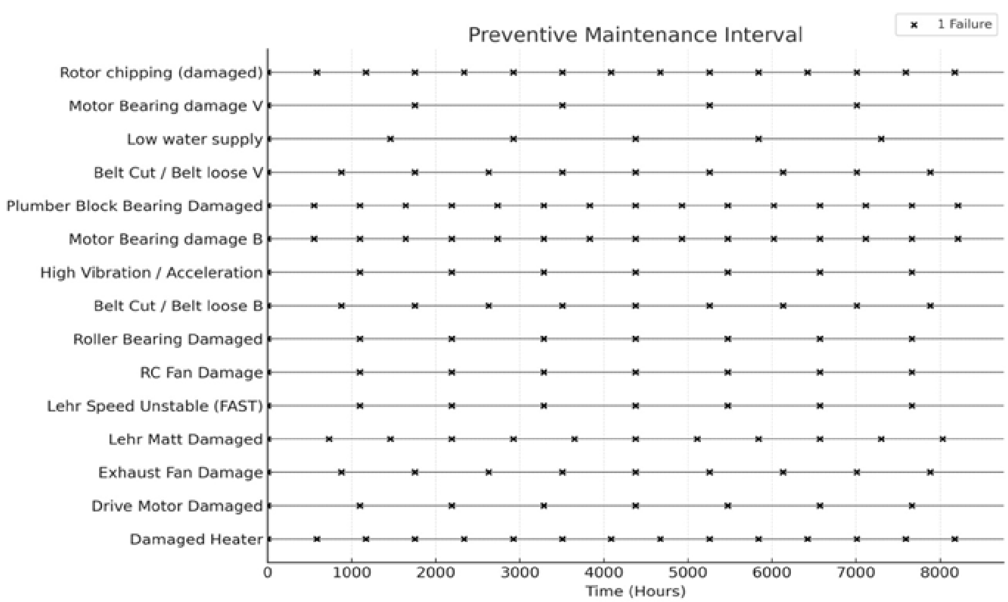

Figure 11. Proposed replacement interval

Downtime can be reduced by implementing the proposed maintenance intervals and ensuring a timely supply of failed parts. Figure 12 illustrates the decrease in downtime following the implementation of the plans.

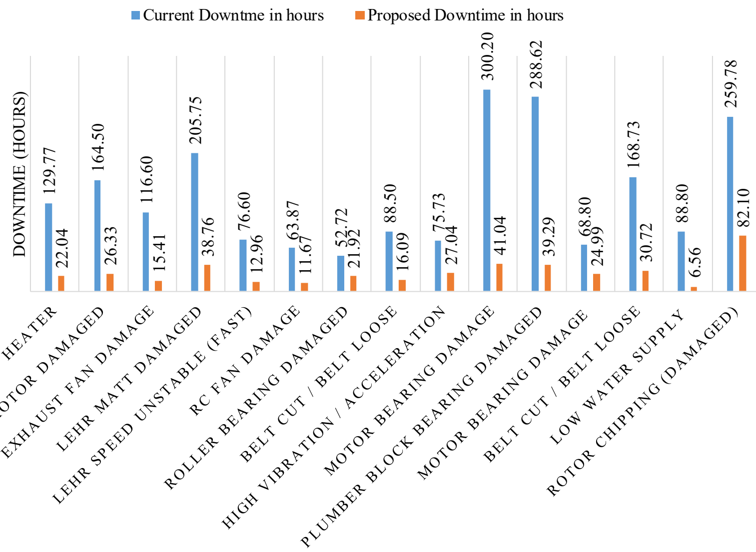

Figure 12.Comparison Between Current Downtime and Proposed Downtime for Failure Modes

Figure 13 illustrates a significant reduction in downtime following the implementation of the proposed maintenance schedule and improvements in spare parts availability. As shown, downtime decreased from 129 hours to 22.04 hours. This reduction is primarily due to more proactive maintenance intervals and faster response times for replacing failed components. As a result, overall equipment availability and operational efficiency have improved.

- **Proposed plan for reducing the defects**

After analyzing the source of the defects, it was found that the breakdown and inspection rooms are the main sources of the defects. Based on the analysis, the following actions were recommended for preventing the presence of defects to reduce defects significantly:

1. Swabbing Process Optimization: Swabbing should be conducted every 20 minutes to reduce the defect accumulation seen in the current random intervals.

2. Preventive Maintenance Intervals: Implementing regular maintenance based on MTBF and the number of failures to minimize breakdown-related defects. Figure 13 shows the defects before and after proposing the plan. Figure 12 illustrates a significant reduction in defects following the implementation of the proposed plan to optimize the swabbing process and adjust preventive maintenance intervals. As shown in the figure, for example, the range is from 6077 tons to 13366 tons. This substantial reduction is primarily attributed to the adoption of more proactive maintenance intervals and optimization of the swabbing process. Consequently, overall equipment reliability and operational efficiency have markedly improved.

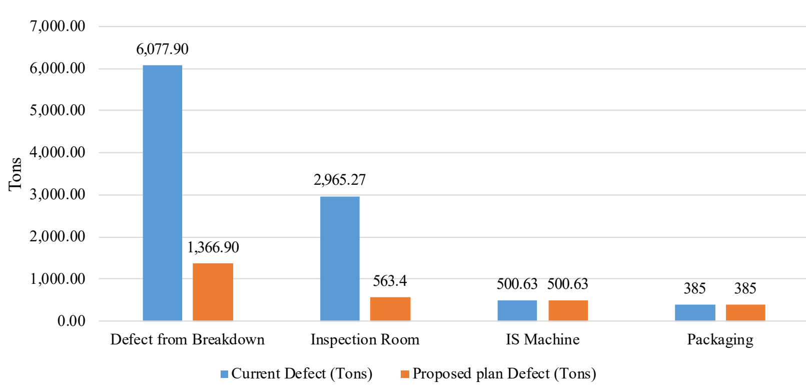

Figure 13. Defect by Area – Current vs. proposed plan

- **Proposed plan for minimizing idling and stoppage losses**

Identification of Idling Losses: After analyzing the causes of idling losses, we identified two main factors:

1. Speed of IS Machine (Mold)
2. Time for Job Change. Figure 14 shows the production losses

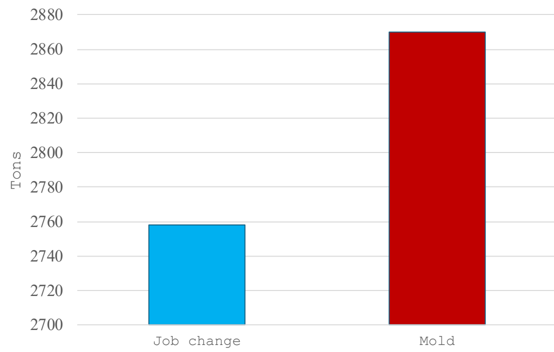

Figure 14. Product losses due to low performance

After analyzing the data, it was found that critical reasons for speed Loss are as follows:

- 6 Molds operating at 210 BPM
- 10 Molds operating at 240 BPM

The production machine has 12 slots for Molds, requiring frequent Mold changes to match the slower 210 BPM speed, reducing overall efficiency.

To increase system performance, the 6 Molds Were Switched to the same type as the 10 Molds, as shown in the cost analysis in Figure 15. "Performance significantly increased after replacing the six molds with 10 molds of the same type. This change enabled higher production capacity, improved consistency, and reduced cycle times. The standardized mold setup also contributed to smoother operations and reduced changeover times. A detailed cost analysis, presented in Figure 16, supports this improvement, demonstrating the cost-effectiveness of the upgrade in relation to the enhanced performance and productivity gains. Additionally, performance increased from 86.1% to 93% after increasing the machine's speed and the number of molds.

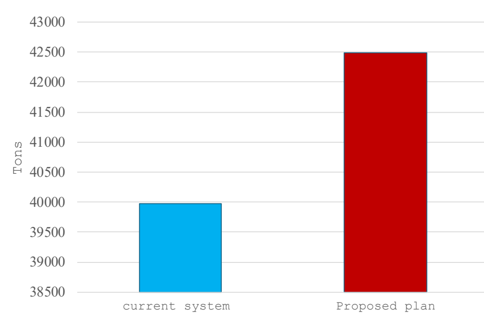

Figure 15. Unit Produced – Current vs. proposed plan

- **Calculating OEE after the proposed maintenance plan**

After implementing the proposed plan for enhancing the OEE, Availability, quality rate, and performance for the current and proposed plans. Figure 16 presents the improvement in availability from 87.73% to 97.62%, which increases the OEE from 56.78% to 63.17%, as shown in Figure 18. Figure 16- Figure 19 illustrates the improvement in OEE, achieved through enhanced performance and quality rates.

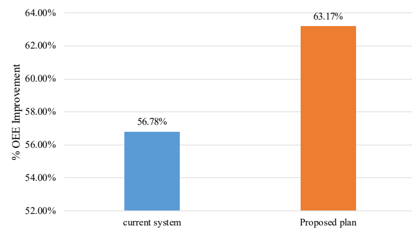

Figure 16. OEE Comparison – Current vs. Improved System (Based on Availability Only)

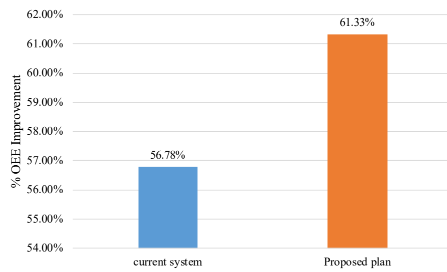

Figure 17. Comparison – Current vs. Improved System (Based on Performance Only)

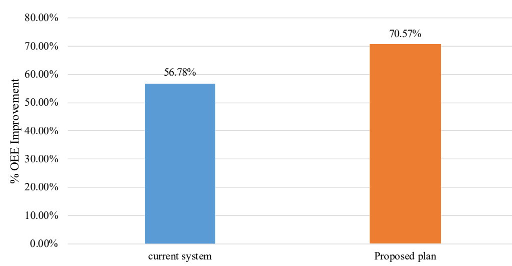

Figure 18. OEE Comparison – Current vs. Improved System (Based on Quality Rate Only)

Figure 19 illustrates a significant improvement in Overall Equipment Effectiveness (OEE), which increased from 56.78% to 84.96%. This enhancement is the result of focused improvements across all three key OEE components: quality rate, performance rate, and Availability. By reducing defects, increasing machine speed efficiency, and minimizing unplanned downtime, the production process became more streamlined and reliable. The combined effect of these improvements has led to a substantial boost in operational efficiency, as clearly demonstrated in Figure 19.

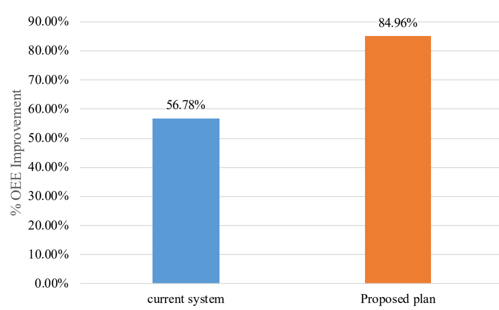

Figure 19. OEE Comparison – Current vs. Improved System

5. Conclusion

This work aimed to improve the overall equipment effectiveness (OEE) of the glass manufacturing line by addressing critical sources of downtime, performance losses, and quality defects. This paper developed a systematic framework based on the reliability-centered maintenance (RCM) approach, an artificial neural network ANN and TPM to identify the primary losses and minimize the high downtime of production machines, thus increasing their OEE. The framework consists of six main implementation phases: system description and critical system selection, critical machine analysis and evaluation, defect assessment, and assessment of idling and stoppage losses. The ANN technique is suggested for assessing the hazard degree of failure modes, determining maintenance mode decisions, calculating maintenance interval cycles, and performing OEE calculations. The developed framework was applied to the glass manufacturing line. Through a structured analysis, significant improvements were achieved. For example, availability was improved from 87.73% to 97.62%, a 9.89% increase. The quality rate increased by 18.26% through improved process control and maintenance planning, resulting in a reduction of defective units. Moreover, a 7.06% increase in performance was achieved by standardizing mold speeds and reducing job change losses. Additionally, there was a 28.18% increase in OEE, indicating a substantial overall improvement in system efficiency. In brief, RCM with ANN provides a more strategic and cost-effective approach. In addition, the developed framework can be used for a maintenance controller system for enhancing the OEE in a production system.

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Biography

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