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Original Article

Optimizing Beverage Manufacturing: Integrating Lean Manufacturing and Machine Learning to Enhance Efficiency and Reduce Waste

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Abstract *- The alcoholic and non-alcoholic beverage manufacturing sector faces persistent challenges that directly impact operational efficiency and business profitability. Recurrent problems in the equipment and sub-optimal practices of operators generate significant waste and production delays. Previous studies have explored methodologies such as Six Sigma, Lean Manufacturing and Kaizen to address these challenges, highlighting tools such as VSM, 5S and SMED. The sector urgently needs to improve operator training and implement advanced monitoring and control technologies to reduce equipment failures. This study proposes a model that integrates Lean Manufacturing and Machine Learning to optimize the production process, reduce line change times and reduce the percentage of waste. Key results showed a significant improvement in production efficiency, with a 42.4% reduction in quality control time thanks to the 5s methodology and a reduction in waste through preventive controls. The implementation of SMED managed to increase production efficiency by 33.3%. The academic and socio-economic impact of this research is considerable, as it provides a practical and applicable framework for improving productivity and competitiveness in the beverage industry. It also promotes economic sustainability by optimizing resource use and reducing costs. Future research must explore new directions for the integration of emerging technologies in the field of Lean Manufacturing, encouraging academics and professionals to continue innovating in the improvement of industrial processes.*

Keywords *- Lean manufacturing, Machine learning, SMED, Beverage industry, Operational efficiency.*

1. Introduction

The beverage manufacturing industry, encompassing both alcoholic and non-alcoholic sectors, faced persistent challenges that directly impacted operational efficiency and business profitability. A notable and enduring problem lay in the constant equipment failures within the production process. These failures, often stemming from suboptimal operator practices, generated a cascade of negative consequences throughout the production chain. "A semi-automatic process caused the process duration to be suboptimal, impacting high-rotation products such as Ready to Drink beverages" [1]. "To achieve process improvement, various methodologies can be applied, such as Six Sigma, Lean Manufacturing, or Kaizen, along with tools like flowcharts, Pareto charts, cause-and-effect analysis, histograms, or control charts" [2]. Despite operators having basic knowledge acquired through experience in semi-automatic machine regulation, precise adjustments crucial for proper equipment functioning were often overlooked. Equipment misalignment resulted in increasing deviations, leading to significant quantities of products destined for reprocessing or disposal. Such recurrent failures entailed substantial economic losses for all industry stakeholders. Primarily, there was a considerable waste of raw materials, as incorrectly manufactured products often did not meet quality standards and had to be discarded. This directly impacted production costs and affected inventory planning and management. Additionally, persistent bottlenecks arising from equipment misalignment rendered production time unusable. This research addresses this challenge by focusing on improving operator training, implementing advanced mon itoring and control technologies, and introducing preventivea intenance practices. Unplanned downtime directly impacted operational efficiency, delayed delivery deadlines, and increased associated costs. Continuous improvement was approached in various ways by industries, especially in the production process, to operate more optimally, effectively, and efficiently [1]. Furthermore, the growth of the Ready-to-Drink (RTD) beverage market added a dynamic dimension. According to Euromonitor, the forecast for 2027 indicated a 50% growth in volume and value, reaching 32 million liters in Peru. The global RTD beverage market has experienced rapid expansion in recent years, generating a growing demand for convenient and ready-to-consume beverages. A report from Euromonitor International revealed a 66% increase in sales in

2022, reaching 16 million liters [3]. In the case study, line changeover times were approximately 50 minutes, representing significant losses as it had more than five products with high rotation. The reduction in line changeover time led to significantly higher revenue generation in the medium and long term. In contrast, the ATE - 2019 Manufacturing Line applied Lean Manufacturing, achieving a significant reduction in quality control times from 55 to 12 minutes, signifying a 78% improvement, as well as a decrease in waste through preventive controls. The implementation of these improvements, especially through the SMED methodology, led to a notable increase in production efficiency, elevating it from 67.1% to 78.9% [4]. Therefore, addressing the issue in the case study, reducing the technical gap, and mitigating its negative economic impact was of utmost importance.

The exploration of practices such as Lean Manufacturing and preventive quality controls was recommended to optimize processes and improve operational efficiency, with the goal of aligning with industry standards and maximizing economic performance. "When applying Six Sigma models, it should be considered that the company must maintain Good Manufacturing Practices (GMP) standards to avoid product contamination, from raw material reception to customer consumption" [5]. The knowledge gap this article addresses lies in the need to integrate Lean Manufacturing tools with emerging technologies, such as Machine Learning, to optimize production in the beverage industry. Despite the widespread adoption of methodologies like Six Sigma and Kaizen, there is a lack of studies exploring how these tools can be combined with advanced data analysis techniques to predict and mitigate operational problems before they occur. This article addresses this gap by proposing an innovative model that not only improves efficiency and reduces waste but also provides predictive capabilities to anticipate and resolve failures in the production process. This research makes a significant contribution to the field, offering a practical and applicable framework for enhancing productivity and competitiveness in the beverage industry.

2. Case Studies and Real-World Applications

In this chapter, the practical applications of integrating Lean Manufacturing and Machine Learning in the beverage industry and other manufacturing sectors will be explored. These integrations have enabled companies to optimize processes, improve product quality, and reduce costs. To illustrate this, case studies will be included where these methodologies have been successfully implemented to address specific problems. SMED is a strategy that effectively reduces setup times, accelerates production, and minimizes waste. This approach allows for quick results, improved organization, and cost savings. By reducing setup times, increasing production, reducing overtime, and improving availability, SMED and 5S are among the most widely used methodologies. A relevant example is the adoption of Lean Manufacturing by a beverage producer, MNO Company. In this case, the company used tools such as value analysis and process flow to identify and eliminate waste. Additionally, the implementation of SMED significantly reduced changeover times on production lines. They also implemented 5S, which allowed for greater flexibility in the production of different beverages without sacrificing efficiency. “Before the improvement of Single Minute Exchange of Dies (SMED), the actual setup activities are eight activities in total with 34 minutes to finish the setup activities.” [6] “After the Single Minute Exchange of Dies (SMED) improvement, four internal activities were converted to external activities, and the rest of the remaining activities became internal activities.

Then, the total time needed to perform the remaining internal activities is 13 minutes.”[6] “Then, using the 5S method reduces the setup time from 13 minutes into 10 minutes after implementing the 5S method.”[6] In this case, they calculated a significant improvement in Overall Equipment Effectiveness (OEE): “the difference of OEE rate is increasing from April to June 2016 76% to 78%. The calculation of OEE includes the line preparation or setup time.”[6].Secondly, a company in the food industry is exami ned.The key area is the Confectionery line, where a gap in m achinery availability has been identified, with the company u nder study reporting a value of 79.06%.; however, the industry reflects that the value is acceptable greater than 90%." [7]"After applying the SMED tool, the times of each activity of the productive process are carried out. The delay in replenishing spare parts and materials for the machines was addressed with the optimization of activities, and the setup for changing products within the confectionery line was improved"[7]. By using SMED, the times of each activity in the production line were identified and optimized.

In addition, delays in replenishing spare parts and materials for the machines were addressed, which contributed to the reduction of the setup time required to change products within the confectionery line. "The lost setup times were tracked over the two months; from them, the following average data was obtained to see if there was improvement. With this, the decrease in the average monthly installation time is observed by approximately 41%" [7]. The optimization of activities and the improvement in setup times contribute to closing the efficiency gap and could bring machinery availability to acceptable levels according to industry standards. The ARIMA (Autoregressive Integrated Moving Average) model, along with its seasonal counterpart SARIMA (Seasonal Autoregressive Integrated Moving Average), has proven to be a powerful tool for time series analysis, leveraging probability-based methods to forecast future data points based on historical data. This capability is crucial for businesses aiming to make informed decisions, as it not only helps in analyzing and understanding past trends but also provides the ability to predict future events, “Making the best business decisions requires the ability to forecast the future, not just the ability to analyze and understand historical facts" [8] The ARIMA model's simplicity and effectiveness make it a preferred choice in various applications. "Probability based ARIMA and machine learning based methods are widely used in time series analysis" [9], which underscores its broad acceptance and utility. The model's strength lies in its ability to handle various time series data, identify patterns, and generate reliable forecasts. Moreover, SARIMA, a seasonal extension of ARIMA, addresses seasonality in data, providing more accurate predictions by incorporating seasonal effects. "Rather than always using AI techniques, a simply applicable SARIMA model can reduce complexity and make computation simpler. The above analysis suggests that the seasonal ARIMA model works with better accuracy as compared to Holt-Winter's model for the prediction" [8]. This suggests that while machine learning methods are valuable, the straightforward SARIMA model can sometimes offer superior performance, especially in handling seasonal data with less computational complexity.

3. Literature Review

3.1. Good Manufacturing Practices

Currently, companies in various sectors need to develop different methods of management and quality control to maintain competitiveness in their respective fields of activity. [10] The institution regulating food safety is the "Dirección General de Salud Ambiental e Inocuidad Alimentaria" (DIGESA), which is responsible for proposing food safety policies, conducting food safety surveillance actions, managing the sanitary registration process, and proposing standards, guidelines, and protocols, among others [11]. The Good Manufacturing Practices (GMP) methodology is essential to meet quality and food safety standards [12] established by DIGESA. The GMP methodology is based on fulfilling aspects such as location, buildings, machinery and equipment, materials, process control, finished products, laboratories, employees, packaging, labels and product descriptions, storage, maintenance, programs, sanitation, transportation, training, and product withdrawal. [12] Additionally, continuous improvement is approached in various ways by industries, especially in the production process, to operate more optimally, effectively, and efficiently [1].

3.2. 5S Methodology

The lean manufacturing tool called 5S is a workplace organization technique used to organize and create quality in the work environment. [9] This technique can be very versatile, as it can be applied to most work situations in a limited time due to its basic nature. [10] The meaning of each S is detailed below [11]:

- Seiri (Sort): Conduct a thorough evaluation of all work areas, including production, storage, and distribution areas. Identify the necessary elements and equipment for efficient and safe production.

- Seiton (Set in order): Define a specific place for each necessary element in the production area. This includes ingredients, equipment, tools, and supplies. Use clear labeling and signage to identify and locate each item in its designated place.

- Seiso (Shine): Establish a regular cleaning and maintenance schedule for all production areas, including equipment, floors, and work surfaces. Train employees on proper cleaning procedures and the importance of maintaining rigorous hygiene in the alcoholic beverage production process.

- Seiketsu (Standardize): Create clear standards and procedures for all aspects of the production process, from raw material reception to packaging and storage of finished products.

- Shitsuke (Sustain): Foster a culture of continuous improvement and discipline throughout the organization. Provide training and professional development to employees to acquire the skills necessary to maintain and improve established standards.

Additionally, it was found that the implementation of 5S improves product quality, maintenance and safety, reduces costs, and reduces production and setup times. [15] In a case study, the 5S methodology and the Single-Minute Exchange of Die (SMED) methodology were applied in the scaffolding manufacturing industry, resulting in a production increase between 15% and 20% as a result of the combined approach [14]. Also, the implementation of 5S provides tidier and cleaner workplaces, allowing employees to feel more comfortable in the work area [9].

3.3. Machine Learning and Demand Forecasting Application

Currently, there is ongoing global economic instability and uncertainty, causing significant challenges in sales prediction. [16] Accurate prediction helps minimize storage costs and waste (expired products), thus reducing the company's losses. On the other hand, the food industry faces greater difficulty because the products it offers have a short shelf life, and proper demand management contributes to better planning. [17]

With technological advances, different machine learning models have been developed, such as Random Forest Regressor, Gradient Boosting Regressor (GBR), and Long Short-Term Memory (LSTM), among others [17]. In manufacturing industries, thanks to accurate demand prediction, costs such as electricity and raw materials, among others, can be reduced [18]. Additionally, for a small and medium-sized enterprise (MYPE), being able to predict demand adequately results in avoiding the disposal of raw materials and having a better production plan, among other benefits, reflecting an improvement in the company's net profit [17]. A traditionally used machine learning technique is exponential smoothing, such as the Hot-Winters method and the Auto Regressive Integrated Moving Average (ARIMA) model, which uses historical sales with seasonality weights. [17] The ARIMA model is generally used to forecast the demand for consumer goods with a limited shelf life [16]. Also, the SARIMA model, which is an extended version of the ARIMA (Autoregressive Integrated Moving Average) model, will be used when a seasonal component is present. This model is employed to predict time series with uncertain values. The ARIMA model breaks down time series data into autoregressive (AR), integrated (I), and moving average (MA) components. The autoregressive AR component describes the relationship between a current observation and past observations, and the parameter p represents the order of this component. This model is used to capture seasonal patterns and repetitive trends in the data. The SARIMA model is denoted as (p, d, q) (P, D, Q) s, where P is the seasonal order of AR, D is the seasonal order of I, Q is the seasonal order of MA and the seasonal period. Upon reviewing the literature, it is evident that applying machine learning models helps improve the profitability of a manufacturing company and avoid overproduction of finished products. The chosen model for this research will be ARIMA, as historical sales data are available, allowing for a more accurate demand forecast.

3.4. SMED

Single-Minute Exchange of Die (SMED) is a lean manufacturing technique used to reduce machine setup times. [19] The use of this tool has been tested in various sectors, such as health and manufacturing, where a decrease in process times and an increase in productivity were observed. [20] The method is based on analyzing the original condition of the assembly line by observing its state during production and the changeover [18]. Subsequently, internal activities, those performed when the process is stopped, and external activities carried out while the last batch is produced or after the next batch has started, are identified [19]. Finally, as many internal activities as possible are converted into external activities until the expected ten minutes are achieved [19].

3.5. Value Stream Mapping (VSM)

Value Stream Mapping (VSM) identifies the value flow of activities, considering both value-added and non-value-added activities necessary in a production process [12]. This method allows you to capture key information about the entire process and avoid excessive detail that hinders understanding [21]. VSM shows the potential to improve lead time, thus enhancing resource efficiency in the production process [21]. This method enables the observation of the continuity of information and material flow in the process. Additionally, its analysis involves various areas where added value is sought, especially in the manufacturing industry [22]. The result of applying VSM in past research is the improvement of the architecture of Production Planning and Control (PPC). Consequently, there was an improvement in the planning of productive activities in the company that implemented VSM [21]. In conclusion, this method provides insight into the flow of information and materials throughout the entire production process.

4. Innovative Proposal

4.1. Fundamentals

The proposed model was developed to reduce line changeover time and the percentage of waste, including defective products, reprocessing, and faulty labeling. This translated into increased production, allowing the company to meet the changing market demand and consequently increasing the net profit of the company. The literature highlights the use of lean methodologies such as Six Sigma, which enables the identification of factors causing defects and provides suggestions for reducing defective products [23]. Thanks to the literature, it was found that it was possible to combine the tools analyzed in the review to implement lean manufacturing methodologies that focus on reducing line changeover times and waste within the company.

4.2. Proposed Model

The improvement proposal was based on the analysis of literature related to the case studies, from which optimal tools were obtained to address the root problems defined in the problem analysis. Lean Manufacturing tools are often combined to achieve better results. The Deming Cycle will be used to apply Lean Manufacturing tools. This cycle divides the process into four phases or components, allowing a focus on continuous improvement. Figure 1 illustrates how the Deming Cycle will be applied in the alcoholic beverage production process.

4.3. Components of the Mode

4.3.1. Phase 1: Act

In this phase, historical data is considered for analysis of the company's current issues. Firstly, historical data is requested to be analyzed, with the aim of identifying the main deficiencies in the process. Subsequently, causes are identified using a problem tree to provide a practical summary of the fundamental aspects obtained from the analysis. Below is the problem tree diagram found in the company. The problem tree diagram is presented in Figure 2.

4.3.2. Phase 2: Planning

During the second planning phase, an exhaustive process was undertaken to develop an appropriate improvement plan aimed at effectively addressing the challenges previously identified in the company. This plan was based on previously consulted research, allowing for an understanding of successful methodologies and tools in other sectors. These valuable references became a guiding light for planning improvement actions. Additionally, an assessment of Key Performance Indicators (KPIs) was conducted to gain a better understanding of the current situation of the company.

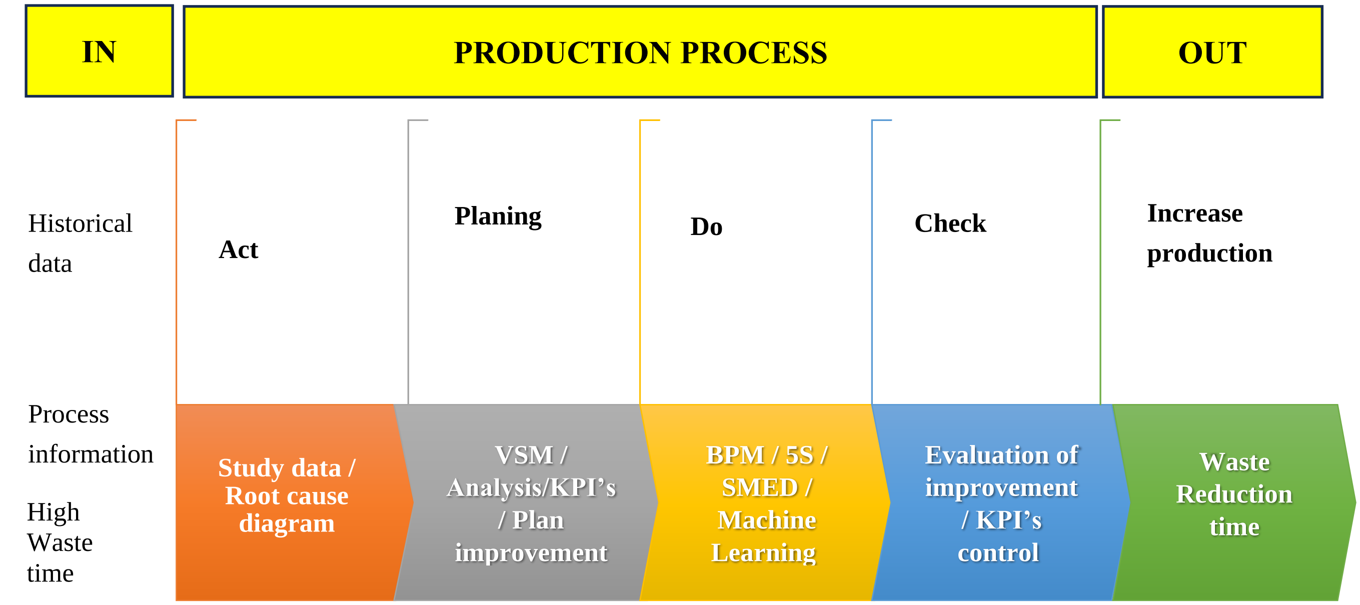

Fig. 1 Proposed model

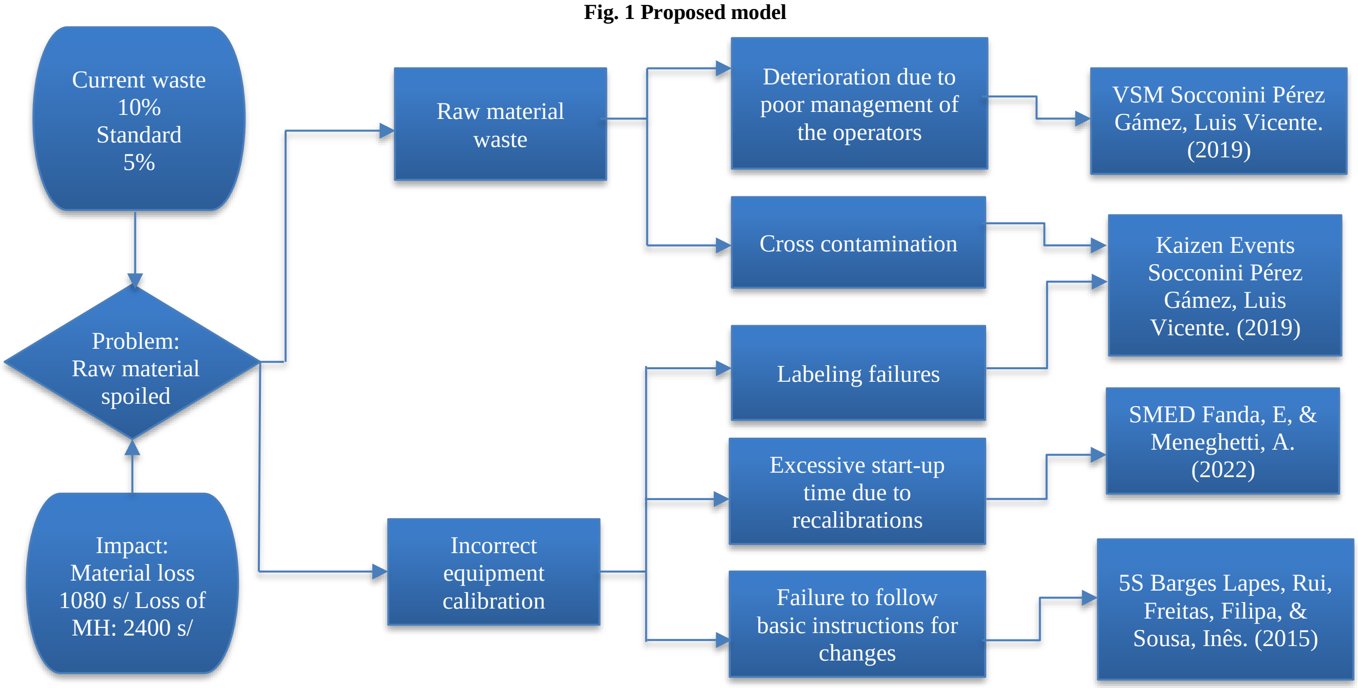

Fig. 2 Problem tree

This evaluation provides a clear insight into critical aspects that require attention and serves as a foundation for identifying specific areas that will benefit from strategic intervention during the implementation of the improvement plan.

4.3.3. Phase 3: Do

During this stage, attention is primarily focused on resolving the previously identified problems. A strategic model was prepared that follows a sequential and meticulous approach to address each of these challenges comprehensively. This model is structured in a logical sequence that encompasses several strategic phases, starting with a detailed analysis through the Value Stream Mapping (VSM) technique, providing us with a complete and systemic view of the current processes. Additionally, VSM helps identify critical points for improving the architecture of Production Planning and Control (PPC) [21]. Subsequently, a demand forecasting model was integrated, recognizing the importance of anticipating market needs to optimize operational efficiency [16].

The application of Good Manufacturing Practices (GMP) emerges as a fundamental pillar in this model, facilitating the alignment of operational activities with the organization's strategic objectives [1]. Equally important, the 5S and SMED methodologies were implemented, positioning themselves as key elements in our continuous improvement approach [12]. These strategies, focused on organization and reducing changeover times, respectively, significantly contribute to process optimization and the achievement of sustainable operational efficiencies [18]. Together, this comprehensive model reflects a commitment to operational excellence and the effective resolution of identified challenges.

Value Stream Mapping (VSM)

The implementation of Value Stream Mapping (VSM) in the context of continuous improvement and the identification of optimization points proves to be a fundamental strategy. In this process, VSM stands out as a key tool for identifying the value flow of activities, highlighting those that add value and pinpointing those that do not contribute significantly to the production process [12].

This tool enables us to comprehensively capture essential information about the entire process while avoiding delving into excessive details that could hinder overall understanding [21].

Machine Learning

In the food sector, where the brief shelf life of products adds a layer of complexity, effective demand management becomes a determining factor for more efficient planning [17]. Moreover, for a Micro and Small Enterprise (MYPE), the ability to forecast demand translates into additional benefits, such as minimizing raw material waste and more efficient production planning [16,17].

The ARIMA model, specifically, has been highlighted as an optimal choice for this research, given the availability of historical data, enabling a more precise and context-adapted demand forecast.

Good Manufacturing Practices (GMP)

Currently, companies engaged in the production of alcoholic beverages and other sectors face the urgent need to implement rigorous methods of management and quality control to preserve their competitiveness in their respective fields of activity [9].

The adoption of the Good Manufacturing Practices (GMP) methodology emerges as an essential component in meeting the rigorous standards of quality and food safety defined by DIGESA.

This methodology encompasses various critical aspects throughout the production process of alcoholic beverages, such as location, infrastructure, machinery and equipment, material management, process control, final products, laboratories, personnel, packaging, labeling, storage, maintenance, operational programs, sanitation, transportation, training, and procedures for product withdrawal. [6,11] The integration of GMP practices throughout the entire production process of alcoholic beverages not only ensures compliance with regulatory standards but also establishes a solid foundation for innovation and continuous improvement in the quality and safety of the final product.

5S

This highly versatile technique stands out for its ability to adapt to various work situations in a limited timeframe, thanks to its basic nature [13]. The five key components of the 5S, from Santos et al.'s perspective (2023), are detailed below:

- Seiri (Sort): Thoroughly assess all work areas.
- Seiton (Set in order): Establish specific locations for each necessary element.
- Seiso (Shine): Implement a regular cleaning and maintenance program for all areas.
- Seiketsu (Standardize): Develop clear standards and procedures.
- Shitsuke (Sustain): Foster a culture of continuous improvement and discipline throughout the organization.

SMED

The methodology known as Single-Minute Exchange of Die (SMED) is designed to reduce machine setup times significantly [19]. The successful application of this tool has been evident in various sectors, including health and manufacturing, where its implementation has led to a notable decrease in process times and a consequent increase in productivity [20].

The process unfolds by identifying two key categories of activities: internal activities performed during the interruption of the process and external activities carried out during the production of the last batch or after the start of the next batch [19]. Finally, the transformation of as many internal activities as possible into external activities is carried out, aiming to achieve the goal of the expected ten-minute efficient exchange [19].

In the specific context of implementation in the company, this strategic approach not only promises the optimization of machine setup times but also fosters a substantial improvement in operational efficiency and, consequently, enhances the company's responsiveness to the challenges of the production environment.

4.3.4. Phase 4: Check

In the final phase of this PDCA cycle, verification was carried out by monitoring Key Performance Indicators (KPIs) and evaluating the improvements to ensure theefficiency of the newly implemented model. Certain tools, such as 5S, include an audit method as part of their control process, while others, like GMP, focus on indicator monitoring.

4.4. Proposed Process

The model will be made based on the process presented below in Figure 3.

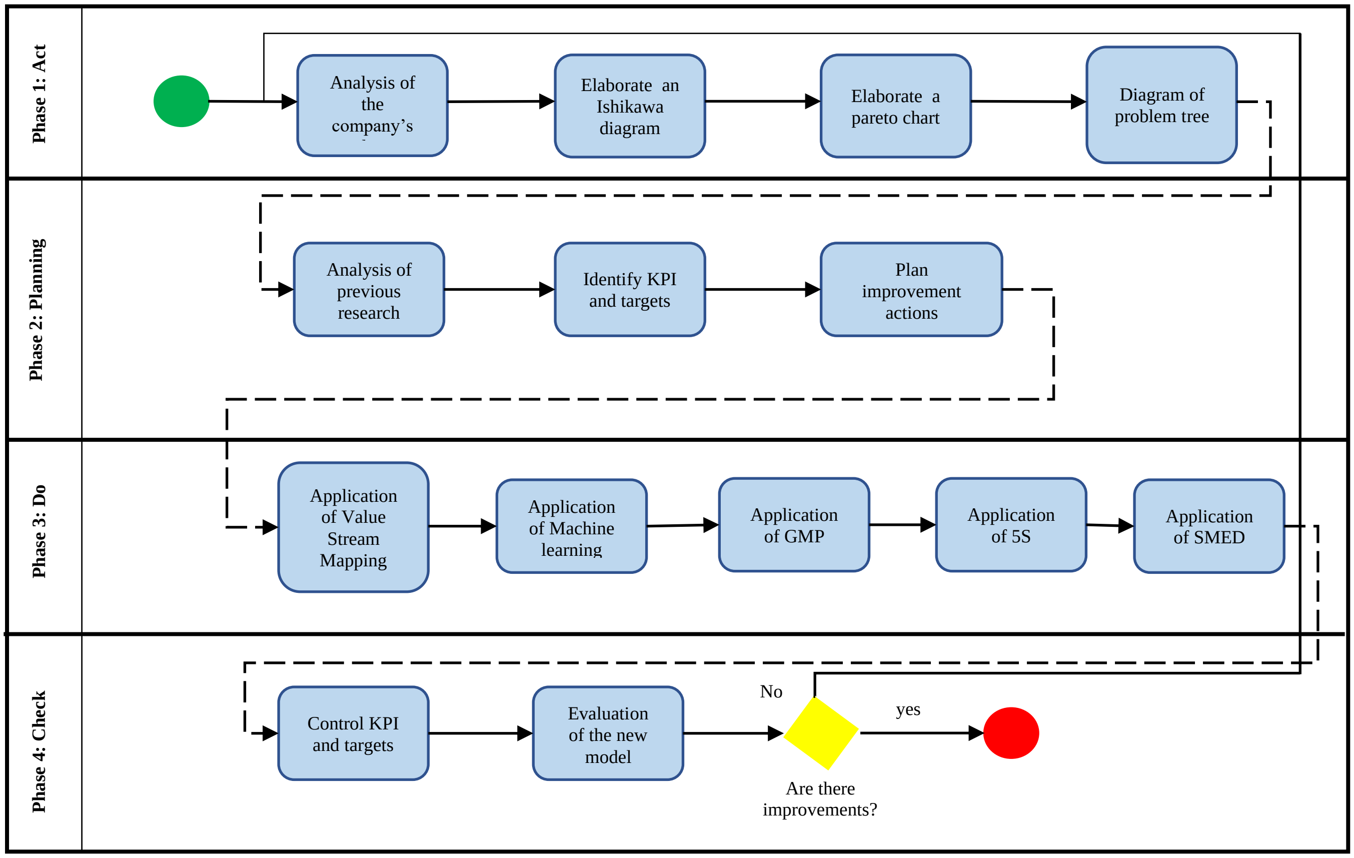

Fig. 3 Proposed process

4.5. Indicators of the Proposed Model

The production cycle time, when used as a Key Performance Indicator (KPI), not only reflects the current operational efficiency but also provides a strategic direction for continuous improvement. A sustained decrease in this indicator can indicate a successful optimization of processes, including the proper utilization of equipment. The ability to use this KPI as a strategic guide allows companies not only to address current operational challenges but also to plan for long-term competitiveness improvement proactively.

$$Production\ Cycle\ Time: \frac{Total\ Production\ Time}{Number\ of\ Units\ Produced} \tag{1}$$

Defective Product Rate KPI enables precise identification of specific sources of defects in the manufacturing process. The reduction of this metric indicates the success of quality improvement. This facilitates targeted improvements and the correction of deficiencies in business production.

$$Defective\ Product\ Rate: \frac{Number\ of\ Defective\ Units}{Total\ Number\ of\ Units\ Produced} \tag{2}$$

The rework rate reflects how often products need to undergo additional processes due to defects or errors during the initial production, impacting not only operational costs directly but also enhancing the efficiency of the entire production chain.

$$Rework\ Rate: \frac{Number\ of\ reprocessed\ units}{Total\ number\ of\ units\ produced} \tag{3}$$

5. Validation

The purpose of this section in the research is to validate the implementation of the proposal mentioned earlier. In this context, the implementation process of each of the previously selected tools is detailed, a system evaluation is conducted using software such as Arena and the Input Analyzer tool, and finally, the obtained results are presented.

5.1. Value Stream Mapping (VSM)

The implementation of VSM will assist the company in addressing challenges in its production process, given that the production planning is currently managed reactively without a robust plan. The implementation of VSM becomes a key pillar in applying a proactive and efficient approach to production management. By visually mapping processes, identifying bottlenecks, and eliminating non-value-added activities, the company can develop a more structured and effective manufacturing plan, focusing on reducing waste, improving demand forecasting, and optimizing change over time [24].

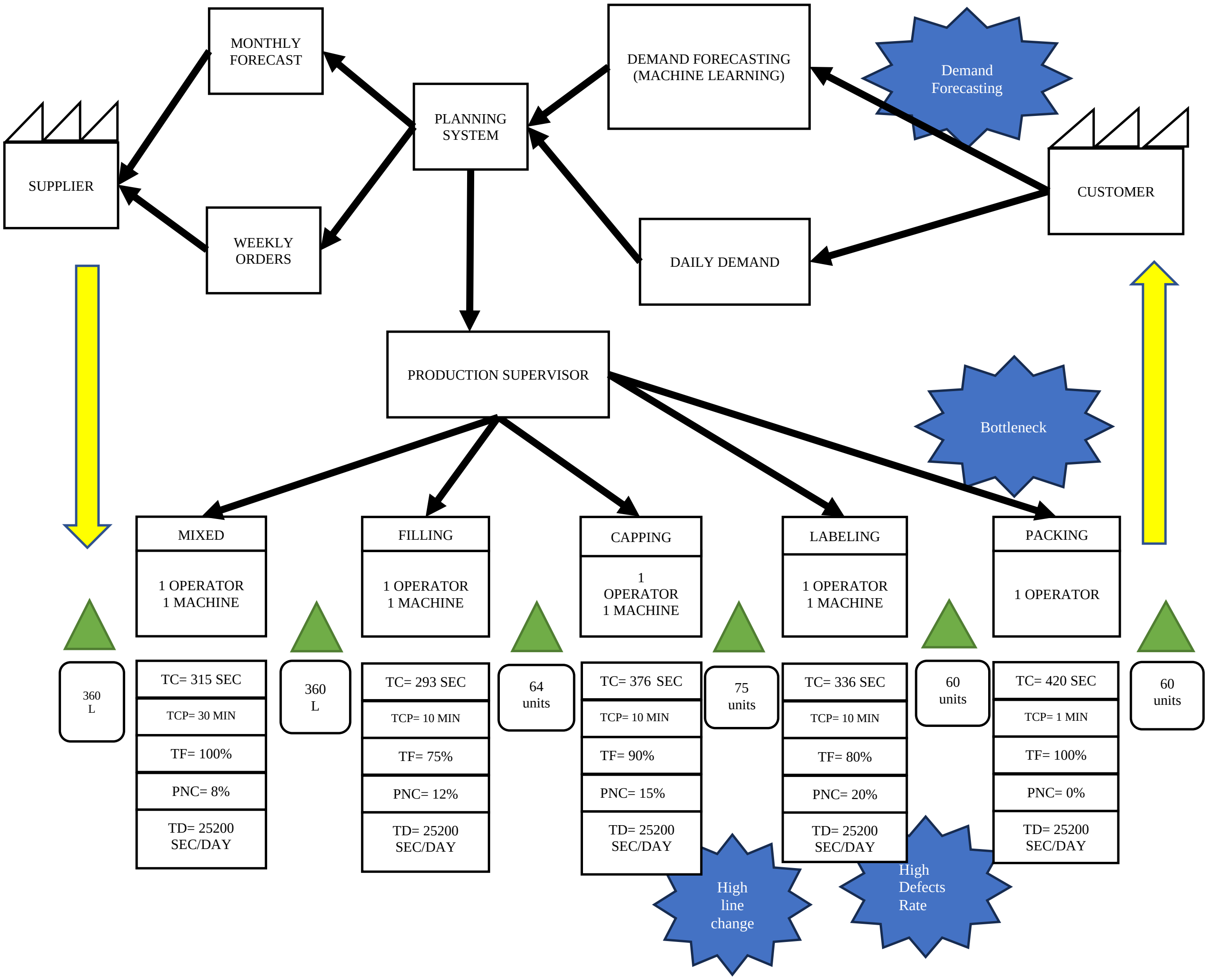

Fig. 4 VSM of the company

Figure 4 illustrates the initial VSM of the company, providing a graphical representation of improvement opportunities. As observed in Figure 4, the company lacks an adequate demand forecast and experiences high changeover time and a high percentage of defects during the labeling process. The main issues concerning the product process include 25% of incorrectly labeled bottles, 18% of improperly sealed bottles, and 12% of reprocessing in the current alcoholic beverage production process.

5.2. Technical Details of the Machine Learning Model

In this section, the technical details of the Machine Learning model applied to optimize manufacturing processes will be elaborated. This includes an in-depth analysis of the various stages involved, such as data preprocessing to ensure the quality and reliability of input data and model training to develop accurate predictions. The validation techniques used to assess the model's performance and ensure its generalization capability to new data will also be discussed. The following libraries were imported for the development of the model:

```python
# Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
get_ipython().run_line_magic('matplotlib', 'inline')
import warnings
warnings.filterwarnings('ignore')
get_ipython().system(' pip install pmdarima')
from pmdarima.arima import auto_arima
```

Fig. 5 Importing necessary libraries

After loading the date and sales data from the last three years to ensure the model has the necessary information and allows for accurate prediction, it is essential to make sure that the loaded data does not contain any null values by using the following line of code.

```
#Ensure there are no null values
RTD_data= RTD_data1.dropna()
```

Fig. 6 Drop null values

Check the data types present.

```
#Recheck the data type
RTD_data.dtypes
```

Fig. 7 Code data type

Convert the month column to datetime.

```
#Convert the month column to datetime
RTD_data['Month']=pd.to_datetime(RTD_data['Month'])
```

Fig. 8 Code to date time

To understand the historical sales pattern, a line chart is created with the X variable (date) and the Y variable (sales)

The next step was to split the data for training and testing the model using the following code.

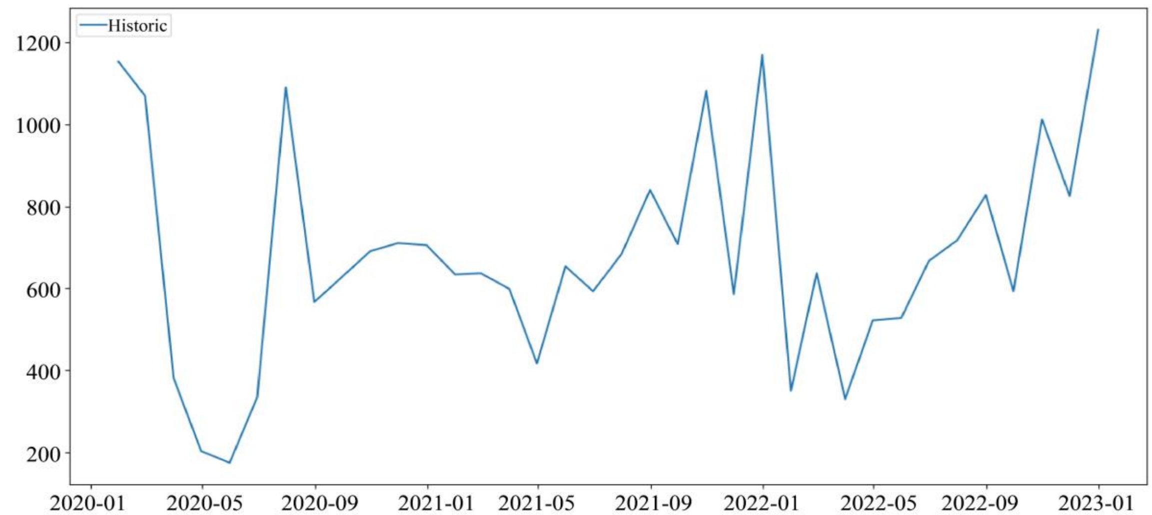

Fig. 9 Sales line chart

```
#Split the dataset into training and testing sets.
train = RTD_data[:60]
test = RTD_data[-20:]
```

Fig. 10 Split data

A line chart was created to understand the training vs test pattern.

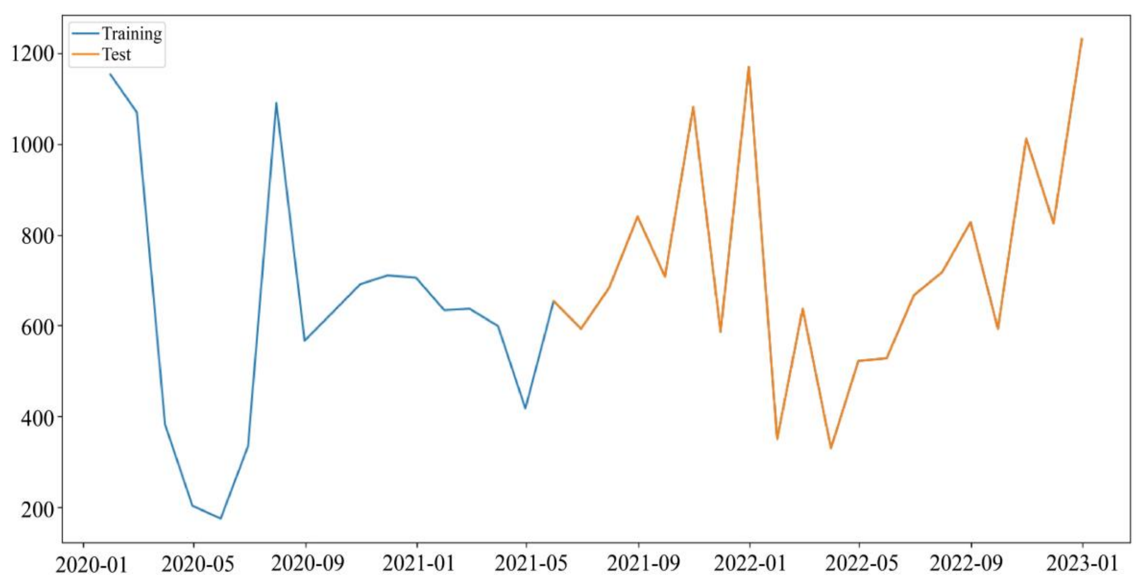

Fig. 11 Training vs test pattern

Moving statistics of the mean and standard deviation are used to define seasonality. Using the following code:

```
#Determine rolling statistics
RTD_data["rolling_avg"] = RTD_data["RTD_Cajas"].rolling(window=12).mean() #window size 12 denotes 12 months,
RTD_data["rolling_std"] = RTD_data["RTD_Cajas"].rolling(window=12).std()  #denotes 12 months, giving rolling
                                                                          #mean at yearly level
#Plot rolling statistics
plt.figure(figsize=(15,7))
plt.plot(RTD_data["RTD_Cajas"], color='#379BDB', label='Original')
plt.plot(RTD_data["rolling_avg"], color='#D22A0D', label='Moving Average')
plt.plot(RTD_data["rolling_std"], color='#142039', label='DesvStd Moving')
plt.legend(loc='best')
plt.title('Moving Average y Standard Deviation')
plt.show(block=False)
```

Fig. 12 Drop null values

By analyzing the moving average, calculated with a 12-month window, data fluctuations can be smoothed out to observe long-term trends.

Additionally, by looking at the standard deviation, it is evident that it increases, indicating that sales were unpredictable during those periods.

In conclusion, considering the moving average and the standard deviation suggests that the data exhibits seasonality.

Thanks to the previous code, the following graph is obtained.

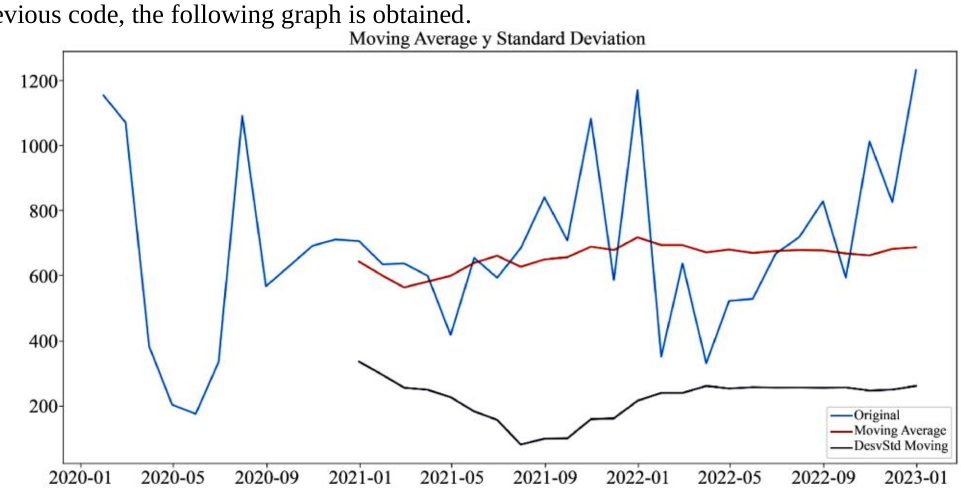

Fig. 13 Moving average and standard deviation

5.2.1. Machine Learning

A stationarity test is performed using the Dickey-Fuller test to detect the presence of a unit root and implement an improvement model properly. The null hypothesis (H_0) of this test is that the time series is a white noise process, indicating that the series is not stationary. If the p-value is greater than 0.05 (p-value > 0.05), H_0 cannot be rejected, and therefore the series is considered non-stationary. On the other hand, the alternative hypothesis (H_1) states that the series is a random walk, implying that the series is stationary. If the p-value is less than 0.05 (p-value < 0.05), H_0 is rejected, indicating that the series is stationary.

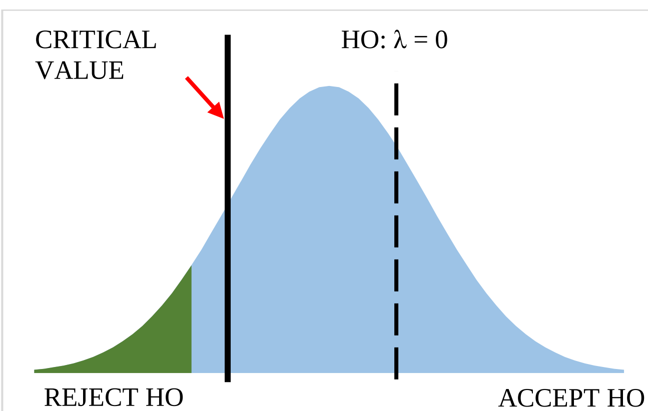

Fig. 14 Dickey-Fuller test

```
#Stationarity Tests
from pmdarima.arima import ADFTest
adf_test = ADFTest(alpha = 0.05)
adf_test.should_diff(RTD_data)
```

Fig. 15 Stationarity test

Table 1. Demand in beverage boxes

Property	Value
Test Statistic	-3.026480
p-value	0.032494
Number of Observations Used	32.000000
Critical Value (1%)	-3.653520
Critical Value (5%)	-2.957219
Critical Value (10%)	-2.617588

H_0: (p-value >0.05) indicates that the series is White noise, and Ho cannot be rejected. Thus, the series is not stationary.

H_1: (p-value < 0.05) The series is a Random Walk, rejecting Ho; thus, the series is stationary.

In the image, the model used in Python to perform the Dickey-Fuller test is shown. The test verifies if the series is stationary or if it needs to be differenced to achieve stationarity. The significance level (alpha) is set at 0.05. Therefore, since the p-value is 0.004153, it is inferred that the series is stationary, and the SARIMA model can be used to make predictions.

5.2.2. ARIMA

The ARIMA model decomposes a time series dataset into autoregressive (AR), integrated (I), and moving average (MA) components. The AR component describes how a current observation relates to previous observations, while the parameter 'p' indicates the order of this component. Similarly, the order of the MA is determined by considering the minimum number of lagged residuals (q), and the integrated component indicates the order (d) of differencing in the time series data [25]. Although the data is probably stationary, given the p-value of 0.004153, an evaluation is conducted to assess how well a standard ARIMA model performs on the time series. From the ARIMA model, various results were obtained, which will be detailed in the following table. The results of the statistical tests reveal that there is no evidence of autocorrelation in the model residuals, as indicated by the insignificant value of 0.00 in the Ljung-Box test. Although the relatively high value of 2.64 in the Jarque-Bera test suggests that the residuals do not significantly deviate from a normal distribution, evidence of heteroscedasticity is observed in the model residuals, as indicated by the value of -0.55 in the Heteroskedasticity test. The plot of the ARIMA model prediction shows a lack of accuracy in the forecasts. Therefore, the use of the SARIMA model will be considered to address seasonality and improve the accuracy of the predictions.

Table 2. Statistical parameters

Test Name	Value
Ljung-Box	0.00
Jarque-Bera	2.64
Heteroskedasticity	0.10
Skew	-0.55

Model: ARIMAX (1, 1, 0) x (0, 1, 0, 12)

```
arima_model =  auto_arima(train,start_p=0, d=1, start_q=0,
                          max_p=5, max_d=5, max_q=5, start_P=0,
                          D=1, start_Q=0, max_P=5, max_D=5,
                          max_Q=5, m=12, method="lbfgs", seasonal=True,
                          error_action='warn',trace = True,
                          supress_warnings=True,stepwise = True,
                          random_state=20,n_fits = 50 )
```

Fig. 16 Code Arima model

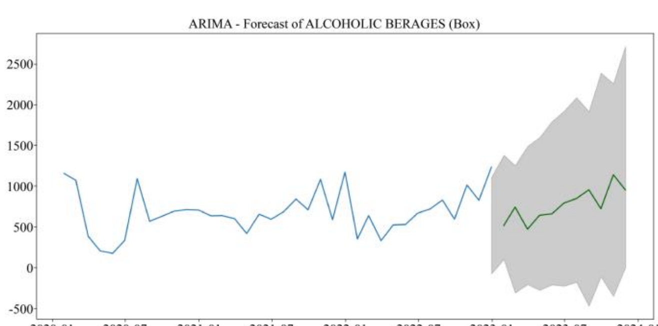

Fig. 17 Prediction arima

5.2.3. SARIMA

Based on the analysis conducted previously, the model selected for demand projection was SARIMA. This machine learning model was employed to analyze and forecast time series data. This approach combines autoregressive, moving average, and integrated components with the calculation of trend and seasonality in time series. This enables the generation of forecasts that fit the model, considering both the historical data and repetitive patterns. In the process of modeling demand forecasting, it is essential to verify the seasonality of product sales. Specific time series data for the products under analysis are used in the context of the SARIMA model. This approach is carried out with the goal of accurately projecting sales, thereby allowing for more effective production planning and ensuring the ability to meet demand efficiently. The following code will be used to obtain the SARIMA model in Python. By incorporating seasonality into the analysis, a demand prediction plot was generated using the SARIMA model. This inclusion of seasonality allows for better capturing of periodic fluctuations in the data, leading to a more accurate and reliable prediction. Compared to the ARIMA model, which does not account for seasonality, the SARIMA model offers a more comprehensive representation of the underlying temporal dynamics in the time series.

```
# Seasonal - fit stepwise auto-ARIMA
SARIMA_model = pm.auto_arima(RTD_data["RTD_Cajas"], start_p=0, start_q=0,
                         test='adf',
                         max_p=5, max_q=5,
                         m=12, #12 is the frequency of the cycle
                         start_P=0,
                         seasonal=True, #set to seasonal
                         d=None,
                         D=1, #order of the seasonal differencing
                         trace=False,
                         error_action='ignore',
                         suppress_warnings=True,
                         stepwise=True,
                         random_state=20, n_fits = 50 )
print(SARIMA_model.summary())
```

Fig. 18 Code Sarima model

Table 3. Demand in beverage boxes

Date	Box Beverage
31/01/2023	350
28/02/2023	637
31/03/2023	330
30/04/2023	522
31/05/2023	528
30/06/2023	667
31/07/2023	718
31/08/2023	828
30/09/2023	593
31/10/2023	1012
30/11/2023	825
31/12/2023	1231
Total	8241

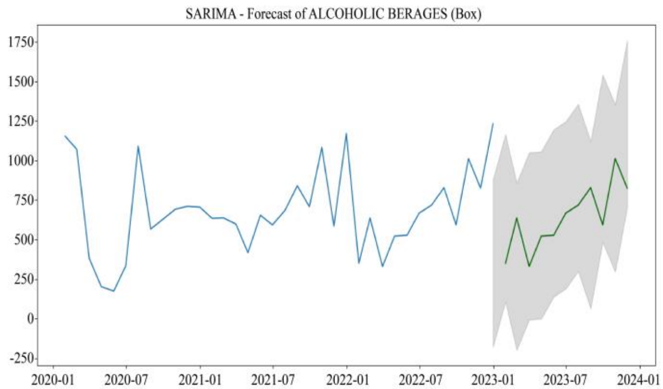

Fig. 19 Prediction Sarima

The company initiates the production of alcoholic beverages upon receiving a new purchase order, maintaining a safety stock of 60 boxes of 12 units. Consequently, during high-demand seasons for alcoholic beverages, such as November and December, they are unable to meet the demand because they lack an adequate production plan, as evidenced by the demand in Table 3.

5.3. 5S

5.3.1. Pilot Plan

To implement the 5S methodology in the alcoholic beverage production process, a pilot plan was designed specifically for warehouses, production areas, and administrative offices.

The main objective of this pilot plan is to demonstrate potential improvements in process efficiency. The central objective of this trial is to highlight how the implementation of the 5S principles can positively impact various critical aspects of the production process.

The reduction of time spent searching for products, efficient organization of production spaces, and the elimination of unnecessary elements will not only contribute to the reduction of waste and reprocessing but will also improve the quality of the final product by minimizing the possibility of improperly sealed bottles.

Additionally, it will be strategically applied to address the line changeover time, seeking a significant reduction in this crucial aspect of the process. The creation of an organized and waste-free environment will facilitate the execution of more efficient and precise line changes.

5.3.2. Initial Audit

Before starting with the implementation, an initial assessment was conducted to analyze the initial state of the company. As observed, the company has a more developed third S, which is cleanliness, as it maintains cleanliness standards during the production process. The other Ss have a lower level because the company has not implemented all 5S. The results of the initial assessment are shown in Figure 20.

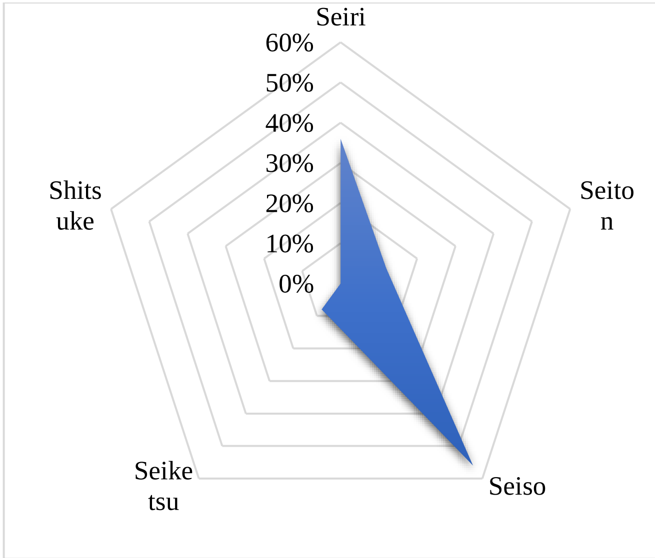

Fig. 20 5S initial evaluation results

5.3.3. Implementation

Seiri - Order

At the beginning of this process, classification criteria are established for objects present in the production area, dividing them into categories such as unnecessary, recoverable, obsolete, and unusable products. Simultaneously, an action plan is formulated that defines the measures to be taken regarding these products: keeping them in custody, repairing, transferring, or eliminating them. Additionally, a specific destination is assigned for each category of objects, whether sending them to the maintenance area, asset management, technical service, document administration, or other relevant areas. As a final step, relevant comments about these products are documented to provide a comprehensive view of their status and situation. This strategy allows for more efficient and organized management of objects in the production area, ensuring that each element is treated appropriately according to its condition and specific needs. Figure 6 shows the current situation in the production area.

Fig. 21 Disorder is observed on the work table, and there are elements unrelated to production

Seiton - Order

The process begins by establishing classification criteria for items in the production area based on their frequency of use. This strategic approach involves assigning specific locations to the most frequently used items, ensuring easy accessibility and minimizing time spent searching. By organizing the work environment according to the frequency of use for each item, operational efficiency is optimized to the fullest. Objects used most regularly are arranged in easily reachable areas, while those used more sporadically can be stored more strategically without affecting daily efficiency. This level of organization contributes to reducing time lost in locating essential items, enhancing the overall productivity of the production area. Furthermore, knowing the location of each item based on its frequency of use establishes a system that promotes workflow fluidity, minimizes potential errors, and facilitates adaptation to changes in demand or the production process. Ultimately, the implementation of the second "S" not only organizes the physical space but also enhances operational agility and efficiency by providing a strategic location for essential items in the production process.

Seiso - Clean

The third "S," known as "Seiso" or "Clean," serves as a natural extension of the established order with the second "S." By implementing the third "S," the goal is not only to maintain a physically organized workspace but also to ensure a clean and unobstructed environment. The implementation of this phase involves the identification and assignment of clear responsibilities for cleaning tasks. Building on the knowledge of item locations based on their frequency of use, as established with the second "S," it becomes easier to determine the specific cleaning details needed for each area. This detailed knowledge enables the effective definition of who is responsible for each cleaning task, which specific areas need attention, and how often these activities will be carried out. In summary, the implementation of the third "S," in connection with the second, is not just about maintaining cleanliness in the work environment but also focuses on establishing systematic practices to ensure hygiene and operational efficiency over time.

Seiketsu - Standardized

The implementation of the fourth "S," known as "Seiketsu" or "Standardize," plays a crucial role in consolidating and improving the previous three "S"s while implementing visual controls that provide clarity on responsibilities and maintenance and cleaning frequencies. Standardization involves clearly defining methods and practices that the entire team must consistently follow. By standardizing these procedures, the continuity of the first three "S"s is ensured over time. Furthermore, the fourth "S" incorporates visual controls to facilitate effective monitoring and tracking of established practices. This includes creating visual indicators that allow team members to quickly identify who is responsible for each area, what procedures should be followed, and how often maintenance and cleaning activities should be performed.

Shitsuke - Sustain

The fifth "S," known as "Shitsuke" or "Discipline," plays a fundamental role in consolidating the previously established practices and promoting a culture of continuous improvement in the workplace. Specific tools will be implemented to strengthen discipline, such as periodically applied surprise checklists and regular training sessions. Firstly, a detailed checklist will be designed to assess adherence to the standards of the preceding four "S"s. This checklist will be applied periodically and without prior notice, with the aim of impartially and objectively evaluating the current state of the implemented practices. Simultaneously, regular training sessions will be conducted to ensure that all team members are fully informed about standard procedures and the requirements of the preceding four "S"s. These training sessions will not only address the importance of maintaining discipline in the application of practices but also provide tools and resources to facilitate the integration of these practices into daily routines.

5.3.4. Final Audit

Six weeks after the implementation of the 5S in the production area, a final audit was conducted to assess the transformation of the state of the 5S. Some operators expressed that maintaining order during the initial days was challenging. However, they noticed that continuing the production process while maintaining cleanliness and order became easier and quicker. In the third week, a training session was conducted to establish specific standards and communicate the vital importance of maintaining organization and cleanliness, especially in areas related to raw material handling and machine cleaning. In Figure 6, it can be observed that the operators' work area is more organized, facilitating their tasks. Inspections in these areas were intensified to ensure they remained in optimal conditions.

Fig. 22 Implementation of 5S Cleaning

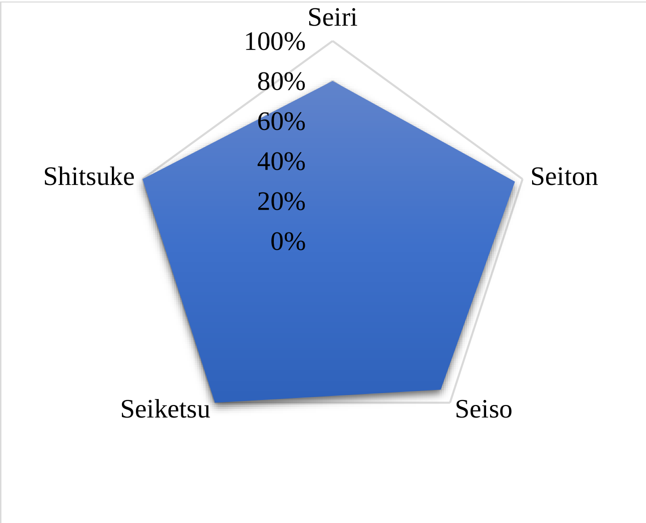

Fig. 23 5S final evaluation results

Table 4. Results of the 5S implementation

Step	Initial Evaluation	Goal	Final Evaluation
Seiri	36%	100%	80%
Seiton	12%	100%	96%
Seiso	56%	100%	92%
Seiketsu	8%	100%	100%
Shitsuke	0%	100%	100%

It is noteworthy that, during this phase, more frequent checks were conducted compared to the initial assessment, and the results reflected the absence of dirt on the floors. These advancements indicate the team's commitment to 5S and its positive impact on reducing waste, improving labeling, and decreasing production times in the specific manufacturing area. Figure 23 shows the final 5S evaluation, demonstrating significant improvement and reaching the expected goal in several S's. To effectively analyze the implementation of the 5S, Table 4 compares the results of both evaluations with the expected goal.

5.4. Good Manufacturing Practices

To effectively implement this methodology, a comprehensive training process was carried out for the employees. Emphasis was placed on the essentiality of incorporating good manufacturing practices throughout the entire production cycle. This approach covered interactions with suppliers to the moment the final product reaches the customer. During the training, the importance of each stage of the process was underscored, highlighting how the application of good manufacturing practices contributes not only to the company's competitiveness but also to compliance with the rigorous standards set by the General Directorate of Environmental Health (DIGESA). Staff was trained on the importance of selecting reliable and certified suppliers, ensuring hygienic and sanitary conditions in facilities, and following standardized procedures at each production phase. The need for rigorous quality controls, measures to prevent cross-contamination, and maintaining detailed records for traceability were emphasized. The training focus extended beyond regulatory compliance, fostering an understanding of how the application of these practices directly contributes to the quality of the final product, food safety, and, ultimately, customer satisfaction. This holistic approach reinforces an organizational culture that values excellence at every stage of the production process, thereby consolidating the highest standards of quality and efficiency.

5.5. SMED

The Single-Minute Exchange of Die (SMED) methodology focuses on reducing tool change times in a production process. Both internal and external activities play a crucial role in this process, contributing to the overall goal of minimizing the time required to transition from one task to another. Table 5 illustrates the internal and external activities involved in the labeling machine. In Table 6, a detailed overview of strategically implemented improvements in the labeling machine process is presented, with the specific goal of transforming internal activities into external ones.

This approach aims to optimize efficiency and reduce the associated downtime with the labeling machine. Additionally, the table highlights how pre-restart PDs have been enhanced, ensuring the proper installation of tools and adjustments. This emphasis on verification significantly contributes to the reduction of potential errors and overall improvement in the reliability of the labeling process. In Figures 13 and 14, the improvement plan implemented to optimize line change times on the labeling machine can be observed. The combined application of SMED methodologies has supported this initiative. The SMED implementation has focused on identifying and converting internal activities into external ones, thereby reducing the time required to adjust configurations on the labeling machine.

5.6. Simulation Software in Aena

The present software was used for its capability in process modeling and simulation, process optimization, decision-making, research, and strategic planning [26]. This resource enables the virtual reproduction of operational scenarios, allowing the evaluation of the effectiveness of implementations in a controlled environment. Through accurate simulations, the impacts on efficiency, production times, and resource management can be analyzed, providing a quantitative and qualitative validation of the improvements made. To create the simulation model in Arena software, a wide variety of data about the production process needs to be collected. It is essential to understand the process to accurately represent it in the flow and identify key activities, as well as to know the inputs and outputs at each stage of the process. Additionally, it is important to know the processing time required for each stage of the process. Once all the time-related data is gathered, it is entered into the Input Analyzer, which provides the variability in the times of the production process. This helps achieve a more accurate simulation. In Figure 26, the simulation model in the Arena program can be observed, which helped validate the obtained results.

5.7. Results

Finally, after the implementation of 5S, SMED, and Kaizen, the case study was evaluated for improvement. The following results were obtained regarding boxes with mislabeled units, poorly capped bottles, and reprocessing. The table analyzes the units from the process without improvement (current process) vs. the process after applying the methodologies (improved process). The following results were obtained in Table 7. In Table 8, it can be observed that defects were reduced by 42.2%. This translates into a significant improvement in the reduction of production time. Additionally, it indicates that the tools used in the process are highly effective. Additionally, the time spent on the line change in the labeling machine was measured, reducing the time from 42 minutes to 16 minutes. This significantly benefited the production process.

Table 5. Internal and external activities

Internal Activities	External Activities
Adjust machine parameters according to the specifications of the new job.	Review necessary documents and procedures for the change.
Shut down the machine safely and efficiently.	Perform preventive maintenance activities to minimize issues during operation and changes.
Disassemble machine parts necessary for the change.	Organize and prepare tools and materials outside the machine before stopping it.
Analyze and improve the design of tools and parts to facilitate the change.	Provide regular training for operators to perform changes efficiently.
Prepare materials, tools, and data needed before stopping the machine.	Perform preventive maintenance activities while the machine is still operating to avoid failures during changes.
Execute the change of tools required for the next process.	
Verify proper installation of tools and adjustments before restarting the machine.	

Table 6. Activity and improvements

Activity	Improvement
Adjusting machine parameters according to the specifications of the new job.	Conducting prior analysis to determine the necessary adjustments for the upcoming job before the machine stops
Turning off the machine safely and efficiently	Developing a procedure to turn off the machine quickly and safely, documenting it, and training the staff on this procedure before the change
Disassembling machine parts necessary for the change.	Designing machine parts to be quickly and easily disassembled
Reviewing documents and procedures necessary for the change.	Implementing marks on the machine to calibrate it correctly
Verifying the correct installation of tools and settings before restarting the machine.	
Analyzing and improving the design of tools and parts to facilitate the change.	Establishing a continuous improvement process where engineers and designers constantly review and improve the design of tools and parts to facilitate quick changes
Preparing materials, tools, and data before stopping the machine.	Designing quick-change systems for tools that can be performed outside the machine
Performing the change of tools necessary for the next process.	Establishing a preparation system that allows materials, tools, and data to be ready before the machine stops

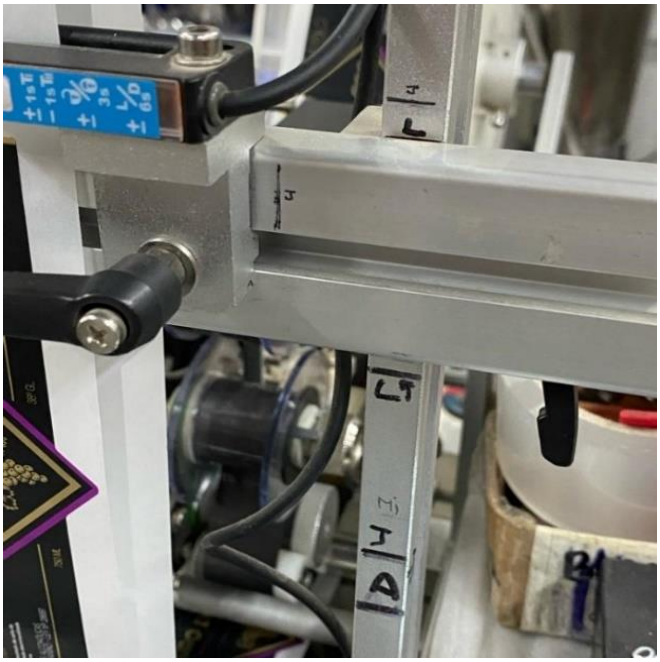

Fig. 24 Implementation of marks to regulate the label detector laser according to each product line

Fig. 25 Implementation of marks on aligners to prevent misaligned labels

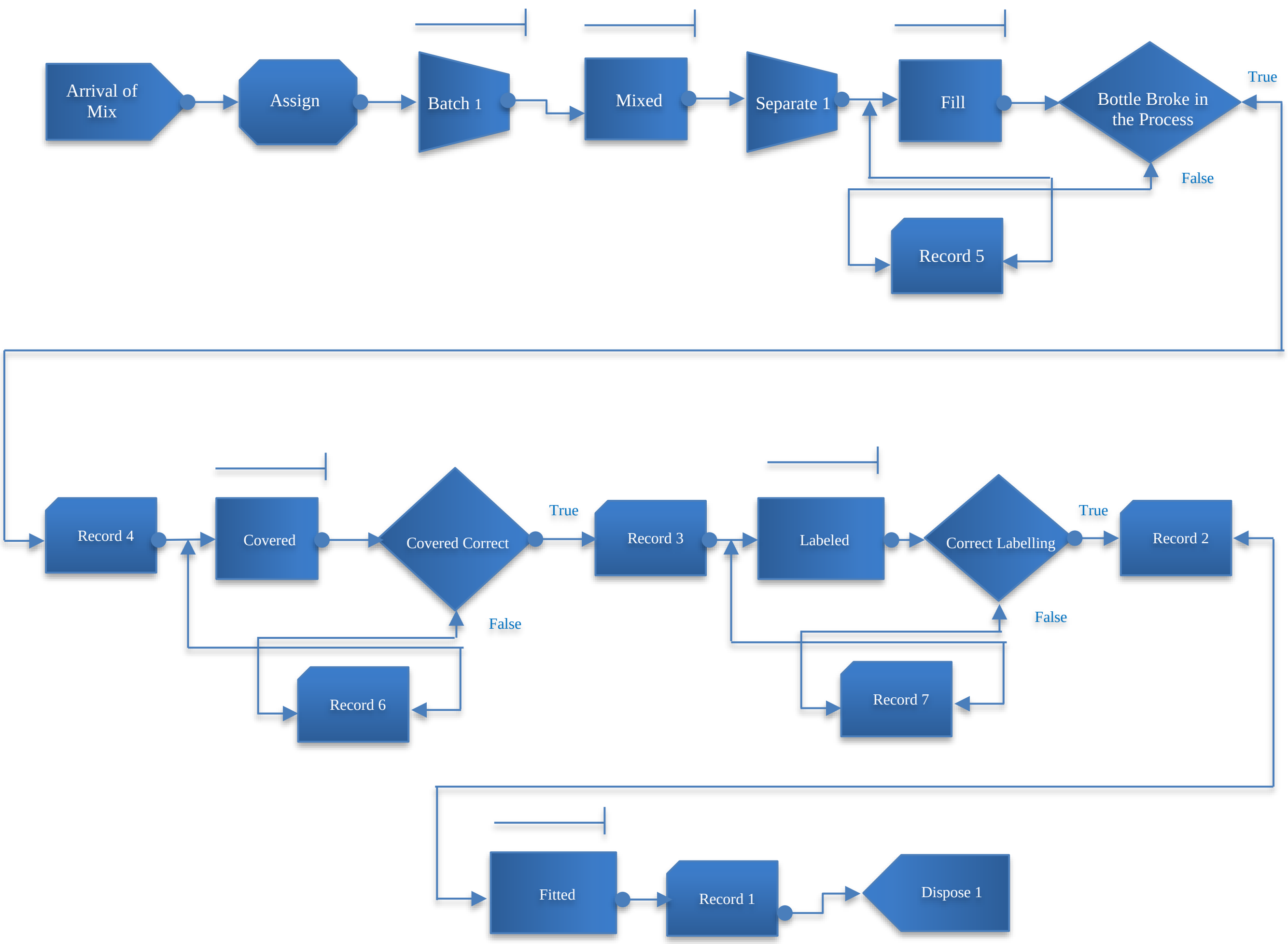

Fig. 26 Simulation model

Table 7. Results of defects

Type of defect	Indicator	Current Process	Improved Process
Mislabeling	Average	15	8
	Standard Deviation	4.3	2.8
Improperly sealed bottles	Average	11	7
	Standard Deviation	3.4	2.5
Rework	Average	7	4
	Standard Deviation	2.7	1.5
	Total Defects	33	19

Table 8. Change times results

	Indicator	Current process	Improved process
Line change time	Average	42	16
	Standard Deviation	4.71	2.02
	Mode	43	19

Table 9. Results of unimproved process vs. Improved process

Description	Unit	Without improvement	Improved
Total time	Minutes	501.98	442.85
Defects During production	Boxes x 12	33	19
Production	Boxes x 12	60	80

Additionally, the total production time was reduced, and the number of defects during production decreased, which allowed for an increase in production from 60 to 80 boxes of 12 units. Furthermore, by implementing the 5S, improvements were observed in terms of order, cleanliness, and classification within the production area.

The implementation of the 5S significantly reduced production times as operators had clear manuals, the workspace was organized, and a philosophy of continuous improvement was applied in the company.

Figure 27 depicts the situation of the case study before implementing the 5S. It can be contrasted with the significant improvement achieved in each of the 5S by the end of the investigation. This positively influences continuous improvement and can be applied to all production lines.

6. Discussion

A series of changes were implemented in the RTD beverage production process with the aim of improving efficiency and productivity. The results obtained during the implementation period revealed a significant impact on the company's productivity, profitability, and customer satisfaction. The key findings are summarized below.

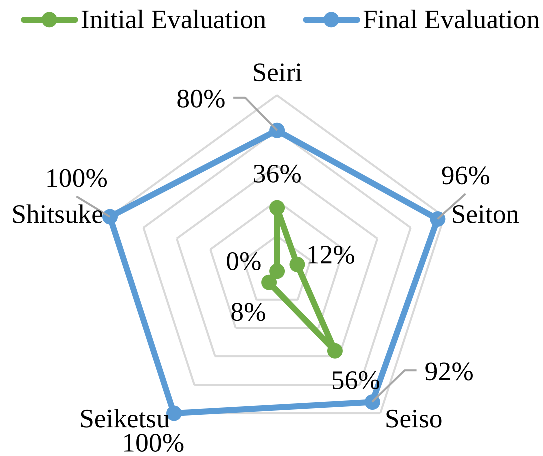

Fig. 27 Initial evaluation vs Final evaluation

The implementation of root cause analysis techniques, regular equipment maintenance, and simplification of the production process led to an increase in RTD beverage production in the last months of the year. This boost in productivity resulted in additional revenues of $18,445, demonstrating the positive impact of the implemented improvements on the company's profitability. The introduction of online quality control systems and specific staff training contributed to a 78% reduction in waste and losses of raw materials and finished products. These changes led to resource optimization and increased efficiency in the production process, further contributing to the additional revenue increase. The optimization of the production process not only increased productivity but also improved delivery times to distributors, resulting in greater satisfaction among customers and strengthening the relationship with distributors.

6.1. Future Directions and Emerging Technologies

To continue optimizing the beverage manufacturing production process, it is important to consider utilizing rapidly developing technologies such as the Internet of Things (IoT). IoT is responsible for creating a network among different devices by configuring nodes and device edges, as well as integrating and aggregating data features through node computing [27]. For example, various data obtained from machines are used for anomaly detection, mechanical failure diagnosis, and other functions [28], which allows for the optimization of the production process.

6.2. Challenges

High-speed and processing-capable sensors are needed to implement sensors that collect information from the different machines. Traditional CPUs cannot perform the processing required for AI [29]. Therefore, an investment in CPUs capable of processing the data extracted from various sensors is required to optimize the production process, as well as price and performance issues associated with the hardware [29].

Thus, it will be important to understand the needs and resources of the company to implement an appropriate plan, which will ensure the necessary software capacity to predict accurately based on a dataset [29] and hardware to store and process data appropriately.

6.3. Limitations

The study presents several limitations from the perspective of generalization and applicability in other contexts. Firstly, the research focused exclusively on a company in the alcoholic beverage sector, which could limit the generalization of the results to other industries or contexts. The specific characteristics of this company and its particular environment may not be representative of other companies in the sector or different industries, affecting the applicability of the findings. Furthermore, the implementation of Lean Manufacturing and Machine Learning methodologies in this study required a specific set of data and technological resources that may not be available in all organizations. The lack of access to advanced technologies and accurate data could limit the ability of other companies to replicate the proposed model and achieve similar results. Another significant limitation is the dependency on the available material and budgetary resources. Budget constraints and the availability of specific resources can vary considerably between different companies and sectors, which could impact the feasibility and effectiveness of implementing the proposed improvements in other contexts. From a practical standpoint, the study's results are also conditioned by Peru's specific time frame and regulatory environment. The regulations and legal standards applicable to the production and marketing of alcoholic beverages may differ in other countries, influencing the generalization and replicability of the study's results. Lastly, implementing improvements based on Lean Manufacturing and Machine Learning requires a high level of training and staff education, which may not be feasible in all organizations due to time and human resource constraints. Resistance to change and lack of staff commitment can also affect the effectiveness of the proposed improvements, representing a barrier to the applicability of the results in other business environments.

7. Conclusion

The main findings of the study indicate a significant improvement in operational efficiency and reduction of waste in beverage production. The implementation of lean manufacturing and machine learning methodologies resulted in a 42.4% reduction in quality control time and a reduction in waste. In addition, production efficiency increased by 33.3%, demonstrating the effectiveness of the proposed model. The importance of this research lies in its ability to address critical problems in the beverage industry, such as high levels of waste and operational inefficiency. These problems, if not resolved, can adversely affect the profitability and competitiveness of enterprises. Research offers a systematic approach to improving these aspects, which is crucial for maintaining competitiveness in a growing global market. Contributions to the field of study are significant, providing an innovative model that integrates Lean Manufacturing with Machine Learning. This integration allows not only the optimization of production processes but also the ability to anticipate and mitigate problems before they occur. The use of techniques such as SMED and 5S in combination with predictive models provides a robust framework for continuous improvement in manufacturing. As for concluding remarks and suggestions for future studies, it is recommended to explore the integration of emerging technologies such as the Internet of Things (IoT) and artificial intelligence to improve the efficiency and quality of processes further. It would also be beneficial to conduct longitudinal studies to assess the long-term impact of these improvements and to explore their applicability in other manufacturing sectors. This study not only provides practical solutions for the beverage industry but also lays the foundation for future research into integrating advanced technologies into manufacturing. The adoption of these approaches can lead to significant advances in operational efficiency and cost reduction, thus contributing to greater economic sustainability and competitiveness in the sector.

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