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A Production Model That Combines Lean And Industry 4.0 Principles To Enhance The Productivity Of Small And Medium-Sized Enterprises (SMEs) In Peru's Food Manufacturing Sector

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Abstract

New technologies, increasing competition, and changing consumer preferences in the food manufacturing sector have forced companies to generate customized products in dynamic demand and thus remain competitive in the market. As a result, companies have had to rethink their processes and product designs to optimize their manufacturing operations. In addition, moving from a conventional production model to processes supported by intelligent systems to generate efficiency improvements in the demand planning and productivity in their activities is necessary. This paper aims to introduce the development of an integrated model of lean 4.0 practices, demand forecasting using SARIMAX and DSS in a manufacturing SME. In addition, a literature review allowed identifying the variables that would be affected, such as inventory, waste, obsolete products, and productivity. Finally, a case study in the food manufacturing sector is considered to validate the model. The results will be presented through a visual analytics dashboard to streamline plant team decision-making.

Keywords

Lean 4.0; Demand Forecasting; Productivity; Machine Learning; Food Manufacturing Sector

1. Introduction

There is growing competition in the industrial sector, where companies are choosing to improve their production systems to make them agile, effective, and precise in the face of the constant changes in the modern world [1]. Bouchard et al. mentions that the emergence of new information technologies, the globalization of climate change, the lack of labor, and changes in consumer preferences have led to dynamic demands and the need for customized mass production systems [2]. With innovation and technological advancement, the increase in productivity has become the current focus, developing various ways of achieving this, but the practices of Lean Manufacturing are the most used [3]. According to INEI, Peru's manufacturing sector contributes 12% of the increase in production [4]. Applying VSM and other related techniques give visibility to the manufacturing production process and allow for balancing the workload, the achievements of which are mainly measured through utilization capacity [5]. In turn, food production in Peru increased (20.6%) during the first half of last year [6]. Food waste is a reality, and it is rare for companies in the sector to focus on reducing it, as it means adapting and modifying their processes [7]. Piras et al. mention that modern industrial food systems are characterized by overproduction, overabundance, and waste [8]. In this sense, it is relevant for companies to incorporate business intelligence tools that allow them to streamline and optimize decision-making through machine learning models to predict demand and, in this way, avoid costs by overestimating or underestimating demand [9]. Finally, several problems negatively affect companies' competitiveness and productivity.

1.1 Objective

This paper proposes a case study when applying the VSM tool with an integrated demand forecasting model with machine learning and DSS to optimize the production of an SME in the food manufacturing sector. In addition, the main objective will be to improve the productivity of a Peruvian food manufacturing company by improving demand forecasting and balancing the workload; in this way, waste will be reduced by overproduction, and loss of sales will be avoided. In addition, the research will conclude with the design of the DSS to monitor relevant KPIs by the plant team.

2. Literature review

This research developed a literature review to find studies related to Lean 4.0 and Machine Learning techniques, according to the research question: What consequences does the application of Lean 4.0 have for the planning of demand and productivity in the sector? In this way, prior knowledge is synthesized, and the state of the art in the food manufacturing sector is analyzed. The databases used to search for the terms were Scopus and Web of Science.

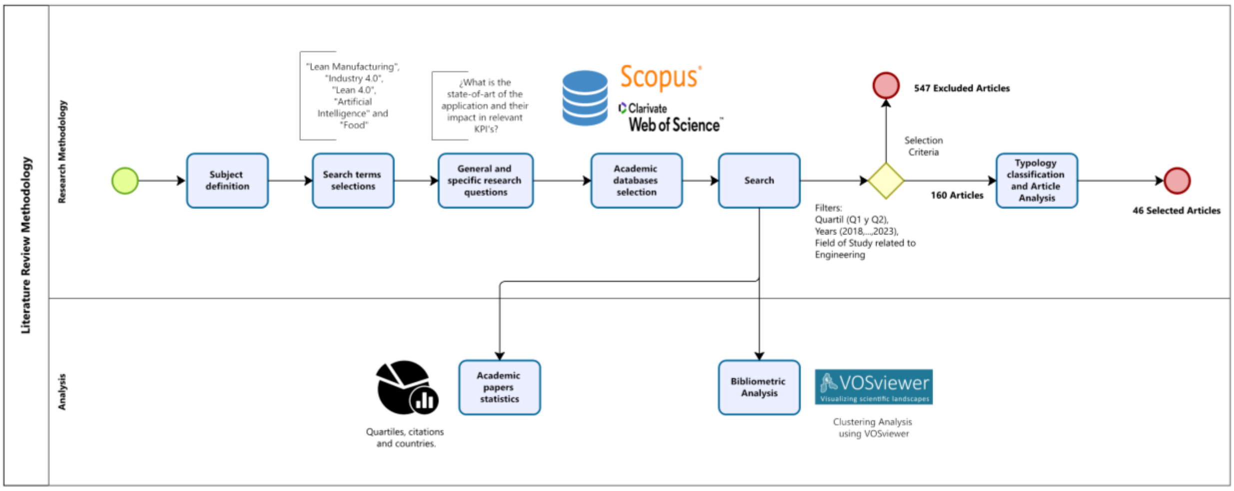

Figure 1: Literature Review Diagram

2.1 Demand forecast using Machine Learning

Using machine learning to make predictions in different business sector areas with a high degree of certainty is becoming increasingly popular. Companies must adapt to today's world, characterized by the need for personalized products, dynamic demand, and stock reduction [2]. In turn, authors Quiroz-Flores et al. implement a predictive demand model using machine learning to reduce the error metric by 9.7% in a poultry production company. In addition, another article identifies a case study in a manufacturing company with a manual process. It uses machine learning to predict the best baking temperature of its products, translating into a better quality of the final product. The results show increased productivity, efficiencies, and a decrease in the company's operating costs [10]. As we can see, there is a similarity between the authors' findings because they mention the advantages of generating a predictive demand model to achieve faster responsiveness to the market and being more accurate in production, better inventory management, and reduced costs due to overproduction or lack of stock.

2.2 Value Stream Mapping in the food manufacturing sector

Implementing production models based on Lean tools is an increasingly common practice. A study developed by Maalouf et al. shows that using the VSM technique allows identifying those productive process activities that are most important and add value, allowing a diagnosis to be made that serves as a basis for reorganizing the system and obtaining increases in productive capacity, reducing cycle times [11]. In turn, the VSM is used in another case study to analyze a company's conventional production system, finding that some activities can be omitted and restructuring the flow through a new map that allows for reducing waiting times and waste [12]. As can be seen, different authors agree that using Value Stream Mapping is adequate to identify those activities that provide value in a production process, being able to modify the sequence and reduce activities to optimize times.

2.3 Decision support system using Dashboards

The challenges of digitizing processes are mainly in using and visualizing large amounts of data collected. Lossie et al. report that Decision support systems (DSS) enable the plant team to be reached with accurate information at the right time. In this way, they designed, implemented, and validated context-sensitive dashboards for operators in production through expert evaluation [13]. In addition, another article presents the importance of giving the values of the most relevant key performance indicators (KPIs) for their monitoring and control. In this way, stakeholders can make better decisions and control actions in the face of changes in production and minimize negative impacts [14].

2.4 Lean 4.0

Lean 4.0 is an approach that combines tools from Industry 4.0 and Lean Production [15]. Although research continues, multiple studies have confirmed that integrating both favors a company's performance and helps reduce operating costs [16]. There is a positive correlation between Lean Production and Industry 4.0, where interaction impacts processes, workers, and organizational efficiency [17]. Approximately 76.3% of all possible pairings of different techniques between both domains have a positive correlation [18]. This makes it clear that it applies in most cases and that specific tools must be selected to improve performance. Research is ongoing, and technological advances will bring in-depth knowledge of the subject.

3. Methodology

In this point, considering the low productivity and level of planning, an inaccurate demand forecast and an insufficient control of the production by the production plant team. The following model is proposed and will assist us in the analysis, improvement, application and validation of the integration of VSM, Demand Forecasting and DSS. The variables to predict is the amount of sales of baked goods using the historical demand.

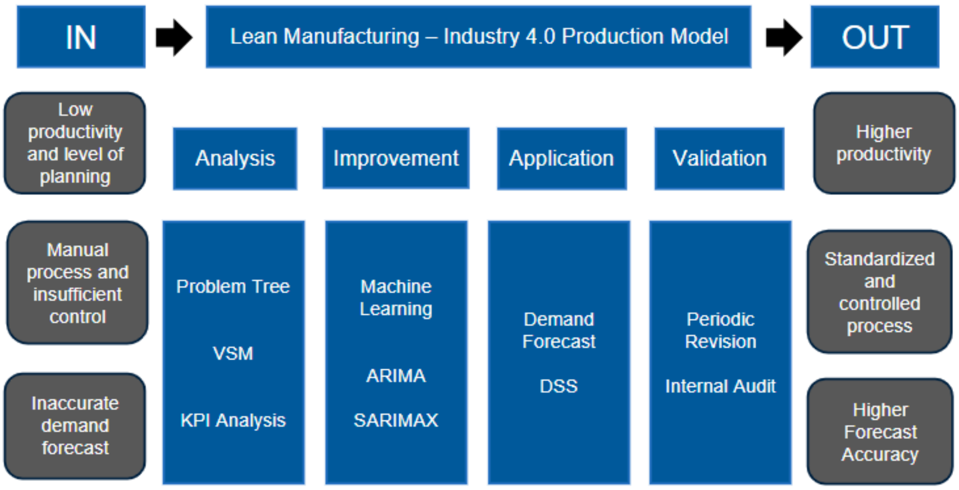

Figure 2: Integrated Model

3.1 Use of VSM for diagnosis in a production process and production of KPIs

Value Stream Mapping is a technique that separates the productive process from the good in all the activities to transform the raw material into the finished product. In this way, essential and critical activities can be separated from those that can be redistributed or eliminated as required. If information collection is appropriate, the time needed for each activity in the process will be provided. In this way, those that take longer are analyzed, being able to analyze the station and its elements to generate perspectives, redistributing space, and reducing or eliminating steps that do not add value to be more efficient [19]. The steps to implement it are Identifying activities and measurement of times, elaborating the map of the current sequence, analyzing the state before the improvement, and designing a future map and an implementation plan. For the present research, a VSM of the company's current state is developed as an analysis and a future VSM, including the proposal for change.

When it comes to baked goods, the main problems encountered are many manual jobs, excessively different times between activities, overproduction, and defective products, for which it is suggested to use the First in, First Out (FIFO) methodology, perform line balancing, automate processes such as cutting and manage inventory [20].

3.2 Demand Forecasting using Machine Learning

For the construction of the demand forecast, this paper follows the CRISP-DM methodology consisting of 6 iterative phases and is the industry standard process in machine learning projects [21]. These will be grouped into four steps, and the model will be built to predict monthly food production. Valuing their results by comparing performance metrics against the current company forecasting method is also essential. In addition, the Python programming language was used due to its open-source nature and the advantages of library availability for easy development.

3.2.1 Business Understanding & Performance Metrics Definition

A visit was made to the company's bakery production plant, and the problem of low productivity and its negative impact on lost sales was identified. In turn, through an analysis of root causes, it was identified that 22% of the problem is due to a poor estimate of demand. Its root is due to an outdated forecasting method by the company, directly affecting the production planning process since it is susceptible to the various variations that occur in demand generating losses and becoming obsolete. Indicators to measure the performance of the predictive demand model will be the coefficient of determination (upper case R squared mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), and root mean squared error (RMSE) to evaluate the time series model. [9]

$$R^2 = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{Y}-\underline{y})^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\underline{y})^2}} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}-y_i| \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}-y_i}{y_i}\right| * 100 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{Y}-y)^2} \quad (4)$$

Where n is the number of observations of the sample of actual production data, capital Y unit vector is the predicted value, and subscript i. is the actual value of production in the period and bar below and unit vector, the final bar below the arithmetic mean of variable Y.

In turn, the Forecast bias [22] and Forecast accuracy [23] of the current demand forecast method will be compared against the suggested model according to the following equations 5 and 6, respectively.

$$Forecast\ bias\ \% = \frac{\sum Forecast}{\sum Sales} \quad (5)$$

$$Forecast\ accuracy = 1 - \frac{\sum Sales - \sum Forecast}{\sum Sales} \quad (6)$$

3.2.2 Data Understanding & Data Preparation

It should be ensured that the information does not have errors, null values, or missing data, ensuring that the data have the corresponding formats for processing through the open-source library of data analysis "pandas." Since it is a time series, the seasonality of the data prepared will be tested by the Augmented Dickey-Fuller unit root test (ADF), this statistical test is the extended version of Dickey-Fuller’s simple test which eliminates autocorrelations between variables and formulates the following null and alternative hypothesis [24].

H0: No seasonality of the data sample

H1: Data sample presents seasonality

To reject the null hypothesis, the ADF test must have a p-value less than or equal to the level of significance used.

3.2.3 Model Construction and Selection

For the construction of the model, pre-processed data will be used. The ARIMA (Autoregressive Integrated Moving Average) algorithm will be evaluated and used for the construction of time series models combining the relationships of historical data with the analyzed observation and its residual error, and SARIMA (Seasonal ARIMA) to develop models considering seasonal and non-seasonal trend data in the time series [25]. The model will be trained with a quantity of historical data (Training data set) while predicting the future time series and evaluating the amount of remaining data (Test data set); in this way, the performance metrics of the model shall be obtained, and the most appropriate model shall be selected [9].

3.2.4 Deployment of the model

Once the trained model is selected with the best fit for the data type, it is executed in a cloud code editor with Python programming language, and the following periods expressed in months are forecast.

3.3 DSS using Dashboards.

A dashboard will be used to analyze indicators and summarize the company's information through the Power BI program. It is a visual tool that allows you to channel large volumes of data, being friendly to most users and facilitating the decision between alternatives. Lossie et al. mention that such a system aims to enable decision-makers to make decisions of the highest possible quality through collecting, processing, analyzing, and providing information and data; this is how large volumes of data can be automatically processed and displayed by the user [13].

4. Case study

On the one hand, the respective diagnosis was made using the Value Stream Mapping tool, which can be found in annexes. The results obtained are summarized in the following table:

Table 1: Value Stream Mapping Results

Category	Operation	Transportation	Inspection	Storage	Delay	Total
Value Added (VA)	10	-	-	-	-	10
Not Value Added (NVA)	-	1	-	-	-	1
Necessary but Not Value Added (NNVA)	-	1	3	2	3	9

As can be seen, there is an activity with the classification that does not add value, as it is not necessary or contributes significantly to the process. The current production situation in the company is characterized by a delay in waiting for cooling after frying. Here, the operators remain to move the product immediately after cooking, leaving it next to the fryers for a few minutes. Therefore, one of the proposed improvements is focused on the product's transport because if the frying is taken directly to the finishing area, physical space is released, and the filling and decoration process is expedited. In addition, a line balance will be made to redistribute and reorganize the workstations as part of the implementation plan. Thus, the time between stations will be as even as possible, increasing productivity. The demand forecasting model avoids overproduction, reducing waiting times and bottlenecks through more accurate projections.

Next, the new Value Stream Mapping is presented, pointing out the solutions to consider in the diagram.

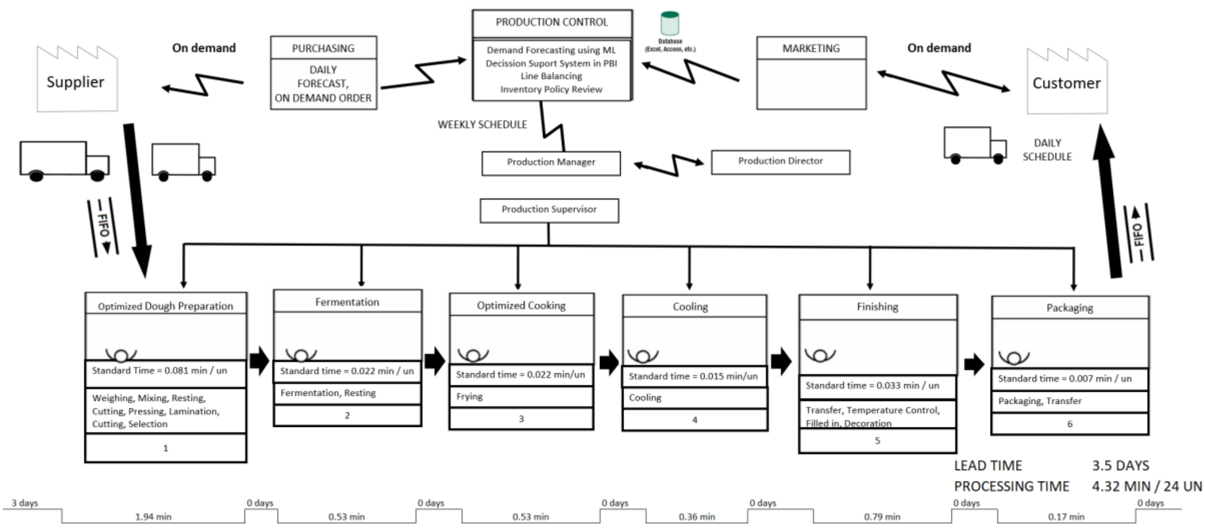

Figure 3: Future-state VSM

On the other hand, the test (ADF) is developed to determine the behavior of the historical production of the bakery product. The null hypothesis of the test states that the data are not stationary. Otherwise, for the data to be stationary, a p-value < 0.05 must reject the null hypothesis. Therefore, when obtaining a p-value of 0.98516, the null hypothesis is maintained; the demand is not stationary. As shown in Table 2.

Table 2: Augmented Dickey-Fuller test values (ADF)

Metrics	Operation
Test Statistic	0.509539
p-value	0.985160
#Lags Used	12
Number of Observations Used	63
Critical Value (5%)	-2.908645

The data set was partitioned into a set for training and validation following a ratio of 67% and 33%, respectively, as shown in Figure 2.

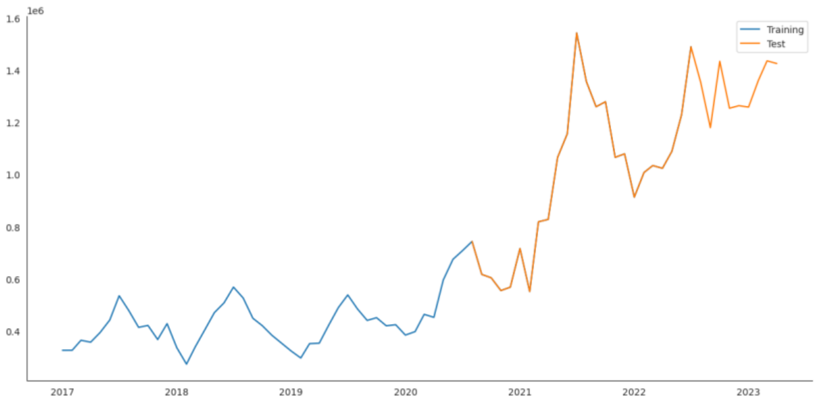

Figure 2: Train set and test set

The performance of the ARIMA vs. SARIMA algorithm is then evaluated, and as shown in Table 3, the prognostic model will be selected using SARIMA. It should be noted that when validating the model's performance using the graphs presented in Figure 3, many data adjusted to the Q-Q positive trend line can be observed.

Table 3: ARIMA and SARIMA Performance Metrics

Algorithm	R-squared	MAPE	MAE	MSE	RMSE
ARIMA	0.912174	0.120384	79891.5547	12753589839	112931.7928
SARIMA	0.922053	0.137624	75934.7801	11318930324	106390.4616

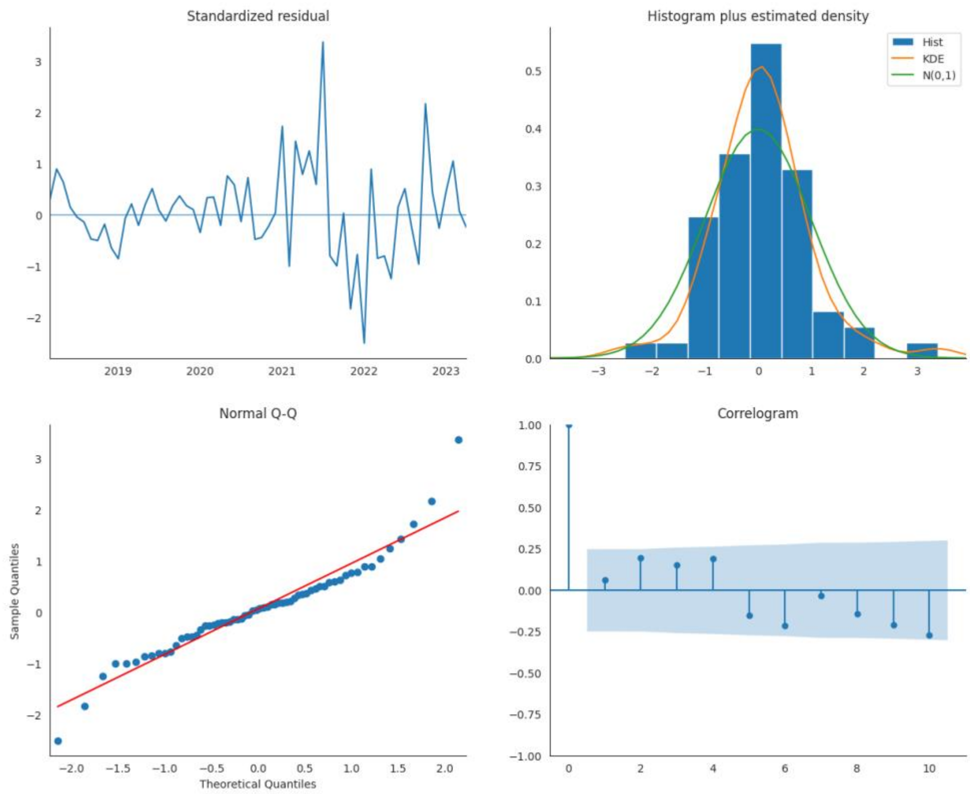

Figure 3: SARIMA model evaluation graphics

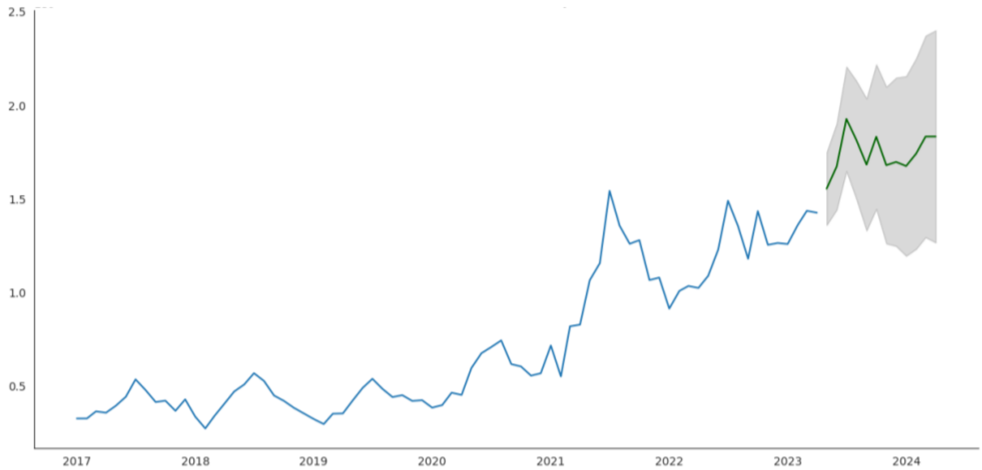

Figure 4: SARIMA – Forecast of Bakery Products

Finally, we evaluated the forecast of demand for the Bakery product of the case study for the next 12 months in units.

Table 4: SARIMA – Forecast of Bakery Products

Date	Forecast of Bakery
05/01/2023	1554093.38
06/01/2023	1672452.3
07/01/2023	1927182.61
08/01/2023	1813367.33

09/01/2023	1682587.07
10/01/2023	1831947.19
11/01/2023	1679416.94
12/01/2023	1697010.72
01/01/2024	1674892.54
02/01/2024	1741611.4
03/01/2024	1832730.78
04/01/2024	1832995.8

5. Results and conclusions

In conclusion, the proposed implementation of an integrated model of lean manufacturing, industry 4.0, and machine learning was validated by diagnosing the company's current situation through the lean VSM tool. In addition, it was identified the time it takes to carry out each activity of the productive process, which, added to the information obtained through the literature review, allowed proposing opportunities for improvement. A literature review was carried out that provided knowledge about the areas of the integrated model, facilitating the selection of tools.

In the case of the demand forecast model, a positive result was obtained with the SARIMA algorithm with a correlation coefficient of 0.922 and an absolute mean error of 75934. Also, it was discovered that the ARIMA model for the data set underestimated the demand value in most cases. Therefore, increasing the forecast accuracy of 93% to 97%. Finally, it is concluded with a dashboard designed with the requirements previously raised to monitor and streamline the decision-making of the plant team.

Moreover, VSM and Machine Learning tools have a positive correlation, so their work together allows to identify the current situation of the company and plan production more precisely, reducing waste and eliminating unnecessary activities to increase productivity.

Nevertheless, further research is necessary to improve the SME production process via Lean Manufacturing tools such as 5S and Standardized Work

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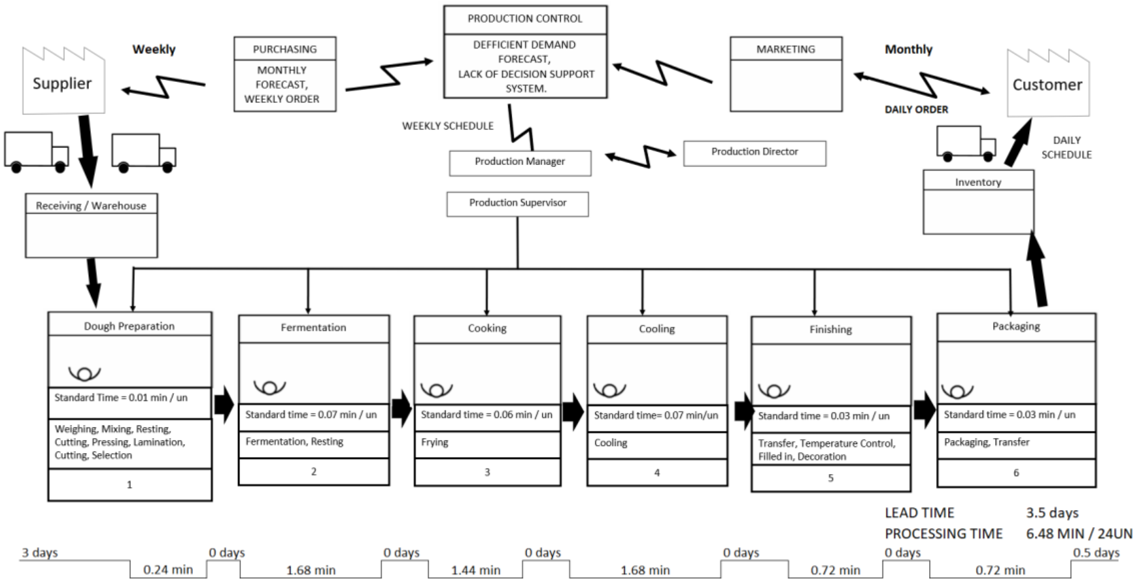
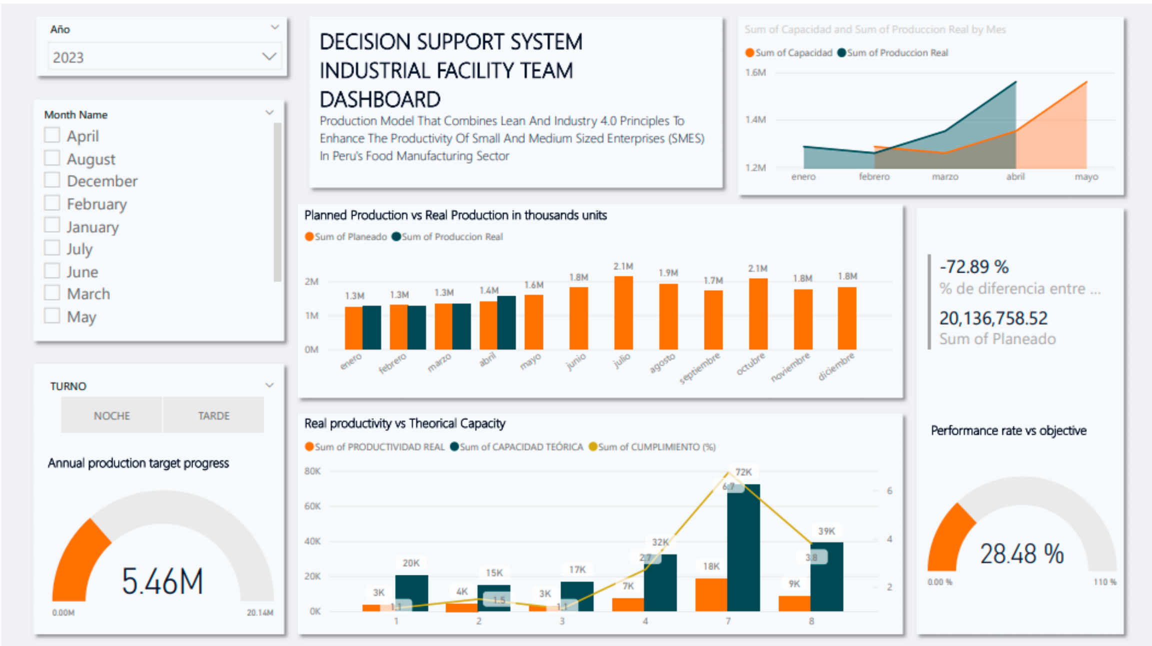
Appendix



Appendix 1: Current-State VSM



Appendix 2: Decision Support System, Industrial Facility Team Dashboard

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Biography

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