Lean Logistic and Demand Planning Model

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Abstract

Order picking and warehouse management is a key activity in any replenishment strategy. An inventory management model is proposed which can be managed through indicators such as order picking time and inventory turnover. For this purpose, a combination of different methods such as ARIMA forecasting, economic lot sizing (EOQ), 5S strategy and ABC technique were combined and taken to a simulation through ARENA software. Finally, the MAPE indicators were reduced from a range of 47.44% up to 79.39% to range of 5.93% up to 37.47%, which is the result of an initial situation versus a later improved one, as well as an increase in inventory turnover and a reduction in total order preparation time.

Keywords
5s strategy, ARIMA forecasting, EOQ, ABC, order picking

1. Introduction
In these times of globalized competition, the supply chain of commercial business models must respond to the dynamic requirements of the market through factors such as integrated inventory management, lead time reduction and supply chain agility (Singh, 2015); on the other hand, according to Staudt et. Al (2015), it is also important to highlight dispatch time and inventory turnover of products that make up these dispatches. These are configured within the internal logistics of a company, planning, execution and control of the physical flow and internal information, whose purpose is to find the optimization of resources, processes, and services with the greatest possible economy (Pinheiro et al, 2017). This is how, order fulfillment becomes important, since it also includes human resources and the development of this activity in the storage and dispatch area can contribute to design a better order preparation system (Groose,2014). Thus, slotting (storage) and order picking activities that require human capital, are fundamental in the warehouse administration system and supply chain management, as they can represent more than half of the running and operating costs (Duque et al, 2020). Therefore, it is important to study these factors in the commercial sector, addressing problems such as the duration of order dispatch time and product inventory turnover, because these can affect the economic and logistical performance of a company's supply chain. Under these concepts, improvements can be made in certain processes and measured through logistics indicators such as order fulfillment time and inventory turnover (Almaktoom, 2017).

This paper has been structured as follows: Sections 2 and 3 describe the literature reviewed and our research methodology. Section 4 discusses data treatment and collection processes. Section 5 provides results and the improvements proposed. Finally, Section 6 presents our conclusions and recommendations for future lines of research on the subject matter.

1.1 Objectives

This research study seeks to improve warehouse management indicators. For these purposes, the following objectives were defined.

- Increase forecast accuracy to improve supply planning.
- Evaluate warehouse indicators.

2. Literature Review

Demand management is a key process for proper planning of storage operations. A key component of all demand management is the forecast that can be developed through the use of various methods such as multiple linear regression, exponential smoothing, ARIMA methodology to fuzzy logic and artificial neural networks (Alawin et al, 2021: Kim, 2017; Salais, 2020) in order to bring projections closer to the actual demand and due to how dynamic and seasonal this can be according to the type of business, the ARIMA methodology is chosen. This tool proves its worth for planning the sales of different spare parts, from automotive to agricultural or construction machinery (Guimaraes, 2020). Results can be obtained from the implementation of demand forecasting have shown improvements in MAPE indicators such as 1.33%, 15.77%, 9.55% and 8% (Pradita, 2020), i.e., there is a proximity to the real demand. In fact, in one of the case studies reviewed, it was possible to increase its forecast accuracy by up to 49.32% in a model for a type of business also dedicated to spare parts. Likewise, another case study analyzed in the agricultural and construction machinery showed a notable reduction in the inventory cost (Guimaraes, 2020). And even a case is presented in which the ARIMA method is enhanced with the artificial neural networks (ANN) method, achieving a more accurate forecast for the replenishment process in the supply chain (Vargas and Cortes, 2017). In the same way, a comparison of forecasting tools was developed in which methods such as support vector machines (SVM), ARIMA and multilayer perceptron's (MLP) were compared in five different forecasting series, from which it was obtained that, in three of the five series, the MLP method is superior; however, in the other two, the ARIMA method is competitive for its accuracy (Velasquez et al, 2010). Therefore, past research shows that there are possibilities of improving demand forecasts in companies of the commercial sector dedicated to the sale of spare parts.

For the correct control and planned replenishment of lean inventories, tools from lean logistics will be necessary. One of these originally comes from lean manufacturing and is the 5s strategy which consists of 5 pillars: organization, order, cleanliness, standardization, and continuity. The implementation of this tool has provided positive results and cases have been evidenced where, after an audit in week 20, a score of 55 was obtained and, subsequently, after 24 weeks, a score of 72 was obtained (Gupta, 2016; Gupta 2020), which leads to improvements such as in the time to search for tools and the level of safety. Additionally, another research showed that the implementation of the 5S strategy can develop the improvement of indicators such as labor productivity, work safety and organizational climate (Lamprea et al, 2017). Likewise, another tool that can contribute positively to inventory replenishment process is the Economic Order Quantity (EOQ) or economic order size since, it consists of establishing the order size of replenishment of a product in order not to entail high logistics costs or overstock costs (Al-Dulaime, 2019). Therefore, if the EOQ method is complemented with a forecasting method, inventory levels can be optimized (Cardenas, 2020; Yildiz and Raman, 2018). This is important because through inventory control with EOQ it is possible to respond to demand in commercial and/or retail companies and this generates not accumulating immobile stocks in the inventory. Thus, in this way, it is confirmed that, to establish better control over the inventory, use is made of the ABC analysis tool which consists of the classification of inventories of various products of a company according to their importance. Inventory management allows to adequately maintain the inventory register, the valuation of these, the lack of units and, mainly, the excess. It makes evidence of this, a case study in the textile industry in which it was evidenced that, due to lack of knowledge of the importance of its products, the production level of a relevant product was below its peers by 2.56% (Kumar, 2018).

Therefore, companies require relevant inventory policies within the management of their supply chain, as well as the management of key indicators because it will be more accessible to balance concepts such as market share, sales volume, profits, and income of new inventories to the supply chain (Kaorapapong, 2018). Likewise, it is necessary of a proper design of warehouses, number of compartments and the number of items according to their classification by rotation and demand (Yu,2015). In addition, in a case in which the ABC technique and a value stream map analysis were used, it was possible to reduce the time of activities such as scanning, inventory verification and order preparation (Baby et al, 2018); therefore, this is another example of the importance of the time of operations within a warehouse.

On the other hand, in an investigation of the same type of non-stationary demand, it was possible to optimize the level of service to 95% at the level of stock supply, this was possible through an optimization study for inventory costs where the contribution of different methods such as moving average, weighted moving average and exponential smoothing for demand, together with the EOQ methodology demonstrated a good level of effectiveness (Pulido et al, 2020). In another research, it was proved that the implementation of the 5S methodology and ABC analysis in three warehouses of different hospitals, achieved an optimization of 15.7% in terms of space saved, obtaining more free areas for a more agile transit and a remarkable increase of 43% regarding the turnover of their inventories (Venkateswaran, 2013).

Likewise, in another case study, an inventory management system was developed based on the classification of its inventories according to the ABC technique according to its turnover and demand forecast using different methodologies such as moving weighted averages, simple and double exponential smoothing, also achieving an improvement in its service level up to 98% on average over the course of a year (González, 2020).

3. Methods

To verify the improvements to be made, a simulation of the dispatch process is developed using Arena software to show the improvements in the performance indicators of the warehouse process (Abideen and Mohamad, 2021).

The operations that make up the dispatch of products were simulated and, likewise, complemented with information such as the use of resources, both material and human, the number of resources required for each activity and the estimated time. Likewise, with the information on the demand for the products in the last two years and the ABC analysis that was carried out, it was possible to know the value of each product in terms of its rotation and in terms of economic benefit for the company. Regarding warehousing, it could be verified that it is empirically organized, in other words, there is no type of criterion for the arrangement of the products, since there is no knowledge of which are the most relevant and it is not easy to search by product location, which also contributes to the high delays in the dispatches.

Therefore, it was proven how important it would be to implement the 5S methodology to standardize this space. Finally, within the simulation, the supply was modeled using the EOQ methodology as a complement to the ARIMA demand forecast that was also included in the simulation. Implementation phases were established to identify the contribution of the lean logistic model consisting of the 5S strategy, ABC technique, EOQ method (economic order size) and complemented with the demand forecasting tool (ARIMA).

Phase 1: 5s Strategy

The first phase of the proposed model consists of making use of the 5S tool to standardize and, above all, organize the company's warehouse. This will be possible through the fulfillment of the evaluation of the different stages of the proposed tool. First, the condition of the shelves in the warehouse will be evaluated and those that are in an optimal condition for the support of the products will be selected, as well as those that contain the appropriate dimensions to make the storage area more profitable. Then, the products will be sorted according to criteria such as fragility, weight, and volume, since this will allow better handling of the products and avoid incidents when handling them inside the warehouse. Then, a regime will be established to ensure the cleanliness and organization of the area, i.e., it will be properly signposted in terms of rules and classification labels by type of product. The purpose of this is that practices within the warehouse are standardized and procedures are managed in such a way that this environment is more practical for the operators. Finally, an audit policy should be established by the warehouse manager, as it is necessary that the improvements implemented are maintained. Following figures show examples of this phase applied in this case of study: (Figures 1 & 2)

Figure 1. Order applied inside warehouse of case of study

Figure 2. Labeling applied in shelves of products

Phase 2: ABC Technique

The second phase of the proposed model consists of applying the ABC technique Figure 3 to the stocks sold by the company to understand their relevance within the inventory turnover rate for the company. First, it is necessary to know all the information regarding the products sold by the company, such as their unit costs, quantities sold within monthly, quarterly, and annual periods, averages, and the variations to which they may be subjected, since they are imported products. Second, inventories will be classified according to their turnover and the profits they generate for the company, and these amounts will be arranged in descending order to subsequently perform the ABC classification. Third, with the figures obtained, the total inventory will be divided with the complete inventory to achieve the classification percentages for products A, B and C (Eraslan and Tansel, 2020).

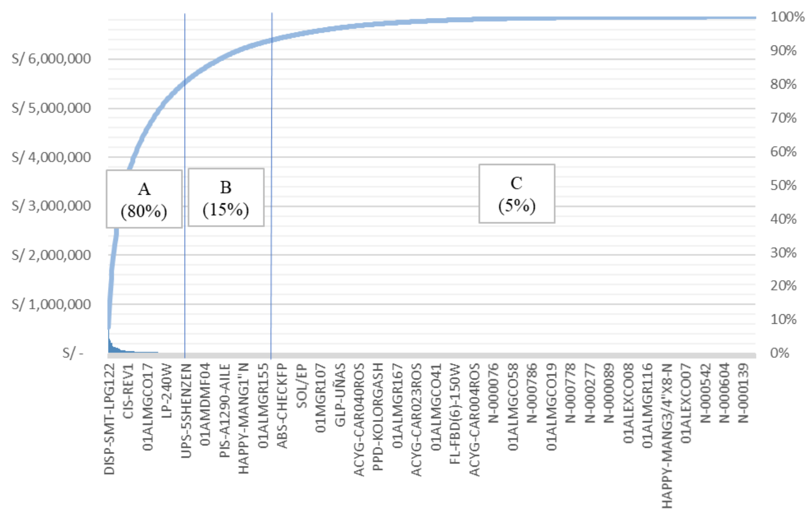


Figure 3. ABC Technique implemented

Phase 3: ARIMA Demand Forecasting

Demand forecasting will be a very useful tool within the proposed model, since it will allow forecasting a demand closer to reality in the future and thus have the necessary inventory, avoiding money tied up for long periods of time. This tool can take different methodologies; therefore, factors such as demand variation, the sector in which the company operates, and the types of products marketed should be analyzed. This is relevant, since it will provide an organized and, above all, standardized data for each item of the organization based on the historical demand provided for the research. This part is called the collection of historical demand data. Subsequently, the demand forecasting model to be used must be chosen. In this case, the ARIMA method (integrated moving average auto regression) was chosen. This method analyzes the data collected to perform correlations between the demand values of previous times. The statistical test "Ljung box test" is performed since it allows finding the correlations between the elements of the time series and the "KPSS test" to determine whether the behavior of the data is stationary or not. Consequently, after obtaining a database of historical demand, the necessary parameters will be estimated in the formulation of the total demand equation to make the prediction and, finally, a demand forecast per defined item will be obtained. First, the difference between demand data with respect to a time is defined, that is, the difference between the demand of one month with respect to the previous one, and this step is repeated for all the data obtained through equation (1):

$$\boldsymbol{I_t = c_{t+1} - c_t} \qquad (1)$$

Where:
I_t = Difference integration variable
t = Time in months
c = Quantity

Subsequently, these differences will be integrated into equation (2) to generate the ARIMA model:

$$\boldsymbol{I_t = \phi_1 * I_{t-1} + \theta * \varepsilon_{t-1} + \varepsilon_t} \qquad (2)$$

Where:
I_t = Difference integration variable
$\phi_1 * I_{t-1}$ = AR (Auto regressor)
$\theta * \varepsilon_{t-1}$ = MA (Moving Average)
ε_t = Current error

Since the above ARIMA equation is used to predict what will correspond to the forecast of the differences of the variable $z_t$variable, it is necessary to return to the variable q to answer what will be the quantities of future demand and, finally, the summation (3) of the values obtained in the variable of the integration of differences is formed:

$$\boldsymbol{c_k = \sum_{i=1}^{k=l} I_{k-i} + c_l} \quad (3)$$

Where:
$\sum_{i=1}^{k=l} I_{k-i}$ = Sum of integrated values (last data period).
c_l = Last data period
c_k = Amount of period to forecast

Phase 4: Economic lot size

Inventory control will be carried out with a supply planning tool called EOQ (economic order size) method. This consists of developing an optimal supply quantity directed to the stocks of the different items marketed by the company. The purpose of this method is to achieve an optimal inventory management avoiding the accumulation of new items. In this way, by obtaining the demand forecast for the different items sold, it will be possible to develop a more accurate replenishment process when complemented with the EOQ method, since the items with the highest utility significance for the company will be prioritized. For this, first the inventory record of each item in the present will be made to know the quantities available and the storage capacity for these items. Then, important data will be determined, such as the time these products will be shipped when they are restocked, the costs of ordering and inventory maintenance, and finally, an inventory planning for the items will be carried out, considering what the EOQ methodology contributes as an improvement to this problem. In addition, it will be possible to define a reorder point considering a safety stock that does not mean a useless inventory. After the establishment of the EOQ method, periodic inventory consultations will be carried out to avoid overstocking or lack of stock. Then, equation (4) will be used to define the order quantity per order:

$$\boldsymbol{EOQ = \sqrt{\frac{2*D*S}{H}}} \qquad (4)$$

Where:
D = Annual demand
S = Cost incurred to place the order
H = Cost of holding inventory

Thus, by performing a daily review of inventory levels, they should be kept above the reorder point (ROP), since by the time this point is reached, ordering should begin so as not to run out of stock (5):

$$\boldsymbol{ROP = d * LT + SS} \quad (5)$$

Where:
d = Daily demand
LT = Lead Time (days to order arrival)
SS = Safety Stock (Minimum Inventory)

Model indicators
Based on the proposed model, it will be necessary to calculate indicators that verify the improvement within the company. The following Table 1 shows the indexes that are considered convenient for such evaluation:

Table 1. Process indicators

Indicator	Meaning/Calculation		Target
Average delivery time	Average time taken to deliver the order to the customer after the order is received		Time < 43 min
Inventory turnover	Number of times of inventory renewal per inventory time	$\frac{Cost\ of\ what\ was\ sold\ in\ a\ certain\ period}{Average\ inventory\ in\ a\ certain\ period}$	Indicator ≥ 0.40
MAPE	Forecast error with respect to actual	$\frac{\frac{\sum_{t=1}^{n}(Real_i - Forecast_i)}{Real_i}}{n}$	MAPE ≤ 50%.

4. Data Collection

Based on the above, it was necessary to organize in advance the steps to be taken to develop the improvement proposal based on the tools specified above. First, it was necessary to collect data at the premises of the company that was the case of the study, whose activity is to commercialize spare parts for fuel service stations and transport vehicles. Regarding the operations carried out by the company where the tools were applied. This to know in detail the essence of each process and what resources are necessary such as people, time, and economic investment. In addition, information was compiled for each type of product registered in the warehouse inventory for the subsequent analysis to be carried out and the historical data of the demand based on the two closest previous years. Also, workers involved in the daily operations of the company were consulted briefly and objectively, especially with the people in charge of the supply, storage, and dispatch process to understand in greater detail not only processes, but also part of the management of this area. After a complete analysis of the entire process to find the reasons for the time losses with respect to dispatch times, the way the products are stored in the space in which they are stored and the way they are distributed, was verified. With the information from the historical data, the interviews with the users themselves and the analysis of the case study, the implementation of the improvement proposal model could be suggested.

5. Results and Discussion

5.1 Numerical Results

After carrying out the simulation of the proposed model of this case study, it should be noted that improvements were obtained in the indicators proposed for the evaluation of the improvement. It is in this way that the historical demand was verified, filtering those demand data that could generate perturbation in its forecasts. In the present case, demand forecasting was achieved with the use of the ARIMA (1,1,1) model, which demonstrates its suitability in the generation of demand forecasts for these items. In one of the cases reviewed, a reduction of the MAPE indicator for the demand forecast of automotive spare parts was achieved by implementing an ARIMA model-artificial neural networks (ANN) which was from 57% to 32.65% (Vargas and Cortes, 2017), compared to the ARIMA model (Table 2) that was performed in this case study, in which MAPE indicators were achieved in a range from 5.93% to 47.44% among the forecasted demands of the 42 items taken into account. It is important to note that the lower this indicator is, the more representative it is and, therefore, the better for the replenishment process, since it will provide a forecast that is closer to actual demand.

Therefore, it is possible to develop a more accurate replenishment with respect to the quantities to be purchased by the company. At the same time, the ARIMA forecasting model offers the possibility of being enhanced with other models such as the one mentioned above. In the same way, satisfactory results were obtained regarding the inventory coverage ratio, the level of service and the inventory turnover, if they are analyzed as an integrated system. These are related since, if there is greater coverage, an adequate level of service will be obtained. When comparing the results, the initial coverage index is higher than the results presented; however, this indicator must be analyzed together with the inventory turnover indicator. This is because, if there is greater inventory coverage, but it is not sold, an accumulation of inventory is generated, which will harm the inventory turnover and, therefore, the company's income will also be harmed. Thus, it is proven that there is an improvement in the inventory turnover rates of the different items in this case after the application of tools such as the 5S strategy and the EOQ method.

Also, as in a case that after simulating what would be the future stage with the implementation of the 5S strategy and the EOQ methodology, it is possible to increase inventory turnover (Venkateswaran, 2013), which suggests that the combination of these methodologies such as EOQ and ABC contribute to inventory turnover. Likewise, in this research case, the "value stream map" (VSM) technique and the ABC analysis were also used to generate a preliminary analysis of the marketed items and the activities that make up the order preparation process, complemented with the 5S methodology, resulting in a reduction of 23.37% in order preparation time.

Likewise, that in another case in which they used the same tools, in which it was achieved that the time of order preparation operations decreased by at least 40% by making use of the same tools (Baby et al, 2018). Finally, it can be assured that the combination of the ABC technique, demand forecasting using the ARIMA model and the EOQ method, served to perform a better supply and the fact that it improves the inventory turnover indicator in warehouses of different types of industry such as those studied in the literature review and that of the present study. Thus, also, the order preparation time is reduced with the elimination of activities that do not add value to the process by repeating activities due to problems of inadequate organization in the warehouse area and which is improved after an analysis using the ABC technique, VSM support and the implementation of what constitutes the 5S strategy.

Table 2. Comparison of MAPES between the ARIMA and Exponential Smoothing forecasting methods.

Product	MAPE		
	ARIMA method	Exponential Smoothing Method	Difference
Article 18	21.65	22.76	1.11
Article 31	47.44	50.7	3.26
Article 2	34.98	38.66	3.68
Article 22	5.93	35.92	29.99
Article 39	41.1	79.57	38.47
Article 41	33.45	71.95	38.5
Article 42	37.47	79.39	41.92

5.2 Graphical Results

First, data obtained from demand for products marketed by the company during the last two years were analyzed. It was observed that there were periods in which some items maintained their rotation at zero, i.e., they were not requested by any customer. Therefore, of the 45 products that were to be considered for the projection, it was verified that some did not meet the requirements to generate the ARIMA model. Therefore, it was necessary to analyze the trends of the historical demands recorded: (Figure 4)

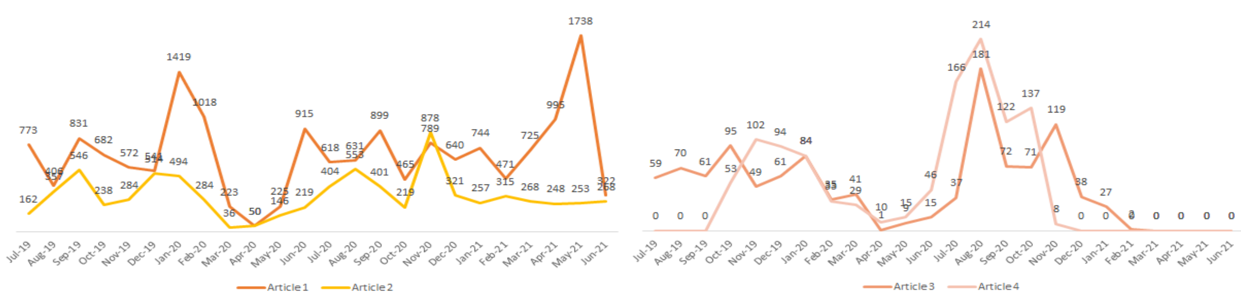


Figure 4. Comparison of historical claims for four items.

As a result of the analysis, it is determined that those demands such as items 1 and 2 in Figure 1 will serve as input; however, those historical demands such as those of items 3 and 4 will not be used, since they present decreasing trends that reach zero for several months, which will be strongly detrimental if the forecasts are applied to them by means of the ARIMA method. Therefore, 42 items considered as propitious for the generation of the forecast are selected and projected to a horizon of five months. These data will serve as input for the simulation in the ARENA software. Likewise, the MAPE indicators of the forecast are estimated and compared with those that would be obtained under the exponential smoothing method.

5.3 Proposed Improvements

As shown in Table 2, the lowest MAPE obtained through the ARIMA method demonstrates its superiority over the other method in thirty-six items out of the total forty-two predicted items.

On the other hand, for simulation purposes using ARENA software, the times corresponding to the order preparation process were estimated by analyzing each task included in the order preparation activity and where there are tasks that do not represent an added value to the process; therefore, they are ignored, since part of the improvement proposal provides a solution to these tasks. Evolution of activity times are shown below in Table 3:

Table 3. Initial and improved status of activity times

Activity	Mean of activity time	
	Initial situation	Improved situation
Reception of orders/Quotation	UNIF(5,10)	UNIF(4.5,9)
Inventory check	UNIF(2,5)	
ERP verification	UNIF(0.5,1)	UNIF(0.45,0.9)
Products picking from warehouse	UNIF(2,5)	UNIF(1.8,4.5)
Validation/ Referral Guide	UNIF(10,20)	UNIF(9,18)
Packaging	UNIF(5,15)	UNIF(0.45,13.5)
Lettering	1*PROCESSED UNITY	

Also, after improvements, indicators are examined in Table 4 which shows the results of the initial situation versus the improved one:

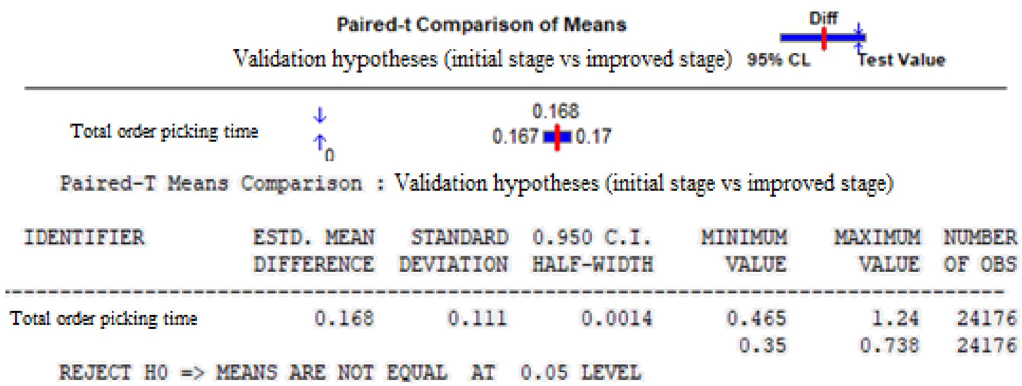
Table 4. Initial and improved status of the indicators proposed for the model

Indicator	Initial situation	Improved situation
Inventory turnover	0.11 - 0.16	0.41 - 5.54
Service level	99.89%	94.02%
Inventory coverage ratio	4.19 - 6.75	0.14 - 0.61
Total, order picking time	43.16 min	33.07 min

There is an improvement in terms of an increase in the turnover rate of selected items and the level of service.

5.4 Validation

Order preparation time decreases by 23.37%, this hypothesis is validated through a paired t-test in which, with a confidence interval of 95%, it is proven that order preparation time can be reduced. Figure 5.



IDENTIFIER	ESTD. MEAN DIFFERENCE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS
Total order picking time	0.168	0.111	0.0014	0.465	1.24	24176
				0.35	0.738	24176

REJECT H0 => MEANS ARE NOT EQUAL AT 0.05 LEVEL

Figure 5. Order picking time indicator: Initial versus improved situation (values expressed in hours)

6. Conclusion

The proposed improvement results increase the annual inventory turnover, because it reduces the number of immobile inventories after making planned supplies; the level of service, because it increases the number of customers properly served; the inventory coverage rate, because it provides a better response to unexpected demands in the supply time and the considerable improvement in terms of order preparation time, so it is proven that the customer will have to wait less to get his order.

In addition, it is possible to generate a reduction in picking times by applying the 5S strategy and the ABC technique to the spaces within the warehouse. Also, a better replenishment process is generated after the optimization of inventory turnover using the ARIMA forecasting method and economic order-lot planning (EOQ).

Therefore, the proposed model would improve the current scenario of the case study on which the research was carried out; however, better results can be obtained if it is supported by another prediction method such as the exponential smoothing used in this case study.

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Biography

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