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*Original Article*

# A Data-Driven Integrated Model for Improving Inventory Turnover in SMEs through Lean Warehousing and Min–Max Policy

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***Abstract*** *- This research focused on a Peruvian industrial distribution SME experiencing low inventory turnover, a typical problem of contexts with high demand change and limited inventory control. While prior works have explored Lean Warehousing and inventory policies individually, integrated efforts are scarce. This research aimed to improve inventory turnover through a data-driven model combining 5S, cycle counting, and a Min–Max inventory policy under continuous review. Following an applied case study methodology, we validated the results of the model through a hybrid strategy that involved a pilot implementation and simulation with the software Arena. A reduced logistics cost of 82%, a decrease in immobilized inventory by 76%, an increase in inventory record accuracy from 86% to 95%, and a reduction of not located products from 45% to 0.4% confirm that the integration of Lean practices with structured inventory policies boosts operational performance of SMEs. Future research may develop more sophisticated forecasting methods and explore the implications of the digital integration of inventory management on more value-added decision-making.*

***Keywords*** *- Inventory Turnover, Lean Warehousing, Min–Max inventory policy, Cycle Counting, Data-Driven Inventory Management.*

## 1. Introduction

The commercial sector has been considered one of the most relevant parts of national economies, and its existence, which constitutes the link between producers and final consumers, is vital for the prosperity of the State. In Peru, for example, the internal commercial sector will reach approximately S/ 49,973 million in total sales in 2024, which represents a growth of 3.8% in relation to last year. Such a sector plays a fundamental role in generating employment, since it provides about 2.6 million jobs and employs some 14.8% of the economically active population. It also generates nearly 4.9% of the national Gross Domestic Product (GDP). All of these represent relevant figures for our country [1]. The hardware and construction finishing sector is part of the commercial industry. Recent reports state that this sector showed a positive performance in 2024, with sales increasing approximately 0.6%. The increase was mainly explained by greater investments in public infrastructure works, the activity of private construction companies engaged in works for other economic agents, and self-construction, which boosted the demand for materials and their derivatives [2]. Other than that, the sector offers important growth potential, and the commercial environment is changing all the time because of transformations in the preferences of consumers, technology, and the increase in competition. These factors force firms to periodically improve by themselves through strategic innovations, optimization of their processes, and by favourably strengthening their proposition. Despite this need, few companies in the Peruvian commercial sector dedicate themselves to innovating processes, mainly due to the time and expense of analysing and improving the processes in their companies [3].

One of the most difficult tasks of a commercial organisation is related to the control of inventories in the supply chain. Firms need to maintain inventories that can supply their customers' demand; however, when they keep more inventory than is necessary, there are costs attached, which must be anticipated and controlled. How many products do you need to hold in order to manage your business efficiently? [4]. Most firms in the sector of commerce do not do an adequate job of handling inventories, and this, through either poor operational performance or poor profitability, can endanger the firms' very existence [5, 6]. Leaving aside the merits of inventory management, many small-and medium-sized enterprises in the economies are uninterested in inventory improvements in favour of other business matters, probably simply because they are unable to understand the merits and power of inventory management improvements [7]. The company analysed in this case study is a commercial small/medium-sized enterprise that sells products related to welding and has three branches locally (Lima, Peru). While analysing the performance, some shortcomings were revealed in the company. The turnover rate for 2024 was 2.38 turnover years. This Figure has been decreasing over the last four years.

The benchmark analysis through the inventory turnover of international suppliers in the industry results in a gap of 32.71% with respect to the sector's average value of 3.53 times a year, where the lowest impact comes from the sector represented by the case study company, with 2.38 times a year and 153.53 days of average inventory duration, which reflects slow movement of the inventory.

The case study company has a low turnover of inventory and operational inefficiencies due to the high percentage of immobilized products and slow-moving overstocked items. Spending for expenses due to a lack of visual inventory control, bad practice on efficient procedure on the control of inventory, and inappropriate purchasing policy and incorrect forecasting, the company also has a Not Located Products of 45%, Inventory Record Accuracy of 86%, and Unsold Stock Ratio of 40%. These contribute to increasing the operating expenses costs while reduces the space in the warehouse that could have been utilized to store useful items, thereby running the risk of spoilage.

Nevertheless, relevant the subject of inventory management is to all commercial SMEs; studies have tended to investigate separately Lean Warehousing as tools to promote and or control inventory or an inventory control model, the combination of the operational and the planning dimension into the unit becomes absent.

The present approaches to tackle warehouse organisation, or the accuracy of products in the inventory, or the amelioration policies of replenishments, adequately has the improvement initiative significantly appealing and successful more especially in subject to a high demand variability, as well as to have difficulties in affording the needed technologies, to sustainably improve.

To this effect, little attention has been paid to the position and part of systematizing, and managing real-time information on influential decisions affecting inventory management, within the context of commercial SME unable to sensibly have broadband adequacy to the digital systems that are advanced capable hence, An important research gap in the development of integrated and a data driven models is hereby established that also synchronize warehouse practices (lean warehousing), inventory accuracy, and replenishment decisions through affordable, as well as scalable achievable technological application.

This study thereafter seeks to improve the turnover of inventory in a commercial SME through the development of a single model applied on the matrix of lean warehousing practices, combining a given close-coupling structuring together and a data-driven technique for decision making. the proposed model comprising of 5S and cycle counting; and Min–Max inventory policy currently under continuous review in the replenishment decisions; and of systematization and digital management of data to an extent that promotes real-time monitoring, alerts automated and more responsive in decision making in operational levels narrow down leaning this integrated way of using analytics, while also, demonstrating industries could improve their turnover rate significantly [8] that shows values of 4.13 and 3.94 respectively turnover on goods for case studies on commercial companies that improved their warehouse and supply system solutions.

## 2. Literature Review

This section outlines the basic theory which supports our proposed approach on inventory management improvement. Studies from previous research related to inventory packing, demand forecasting, and supply policies for commercial institutions, paying attention on engineering tools for warehouse performance and inventory accuracy improvement, such as the 5S tool, cyclic counting, Min–Max inventory policies, etc. For the literature review, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approaches were used to determine which studies were most related to the general research topic. These results from these studies also inform on general problems in inventory packing, such as excess stock, immobilized inventory, and low inventory, for the basis for determining the research gap which is addressed in this research.

### *2.1. Inventory Turnover in the Commercial Sector*

In the studies reviewed, some deficiencies in inventory management were identified within the companies reviewed, and having a low inventory turnover is one of the more frequently stated problems. Poor product rotation can increase the risk of obsolescence and a loss of value of stored products. Generally, these types of issues are attributed to poor management of the warehouse, with errors mainly occurring during certain activities such as registration of inventory or the allocation of products in the storage area [8-10]. Deficiencies in inventory turnover can also result from issues in purchasing management or a lack of demand planning and/or forecasting, which can generate shortages or excesses of inventory.

Some of the studies also presented the (alluded) key performance indicators used to measure if the performance of commercial inventory management is indeed what they expect, as they can be used to assess how effectively, accurately, as well as if logistically successfully the system is despite variances. One of the most commonly used indicators is the Inventory Turnover Ratio, which measures how often you sell out of the products you store per period. Higher amounts of turnover generally mean a more efficient cycle of products and lower carrying costs on that product segment; lower amounts indicate excess inventory and possible financial risk [8]. Another relevant metric is the Location Registration Accuracy, which evaluates whether products are stored in the locations recorded in the warehouse system.

In the studies reviewed, it was emphasized that the importance of maintaining high accuracy in this indicator is to reduce search times, minimize picking errors, and improve operational productivity [5, 8]. Similarly, Inventory Record Accuracy is frequently used to measure the consistency between system records and the physical inventory count. It was highlighted that higher levels of inventory accuracy contribute to reducing errors in order fulfillment and inventory replenishment processes [9, 11].

### *2.2. Lean Warehousing for Inventory Management*

Due to the large number of SKUs typically managed in commercial companies, several studies highlight the importance of first classifying products to facilitate inventory management and improvement initiatives. In this regard, some studies implemented an ABC analysis based on sales to identify the most relevant pharmaceutical products to be included in their study.

This classification was complemented by the Implementation of Lean continuous improvement practices under the PDCA methodology, as well as the 5S technique to improve warehouse organization. As a result, the authors reported a significant reduction in the percentage of misplaced products. Although a Value Stream Mapping (VSM) analysis was not applied to evaluate operational times, the improved organization of the warehouse likely contributed to reducing handling and search times [8]. Similarly, the use of Kanban cards to identify products approaching expiration facilitated better inventory control and product rotation [9].

Other studies have combined warehouse organization tools with process analysis techniques to improve operational performance. For instance, studies implemented 5S and visual management practices to reduce storage and packing times, while also applying VSM to identify stockouts as a major operational problem [10].

Likewise, these improvements were combined with an ABC classification and the use of red tags to identify obsolete items, and applied the 5S methodology in different stages of the implementation process. These combined strategies led to reductions in storage, receiving, and packing times. Similar findings were reported in other studies where it was also emphasized that the role of the 5S methodology as a fundamental element in warehouse improvement processes, ultimately contributing to increased inventory accuracy [11, 12].

### *2.3. Demand Forecasting and Replenishment Policies*

Successful inventory management and planning include the use of accurate demand forecasts for the regular updates of an inventory level. A forecasted demand will help companies when they assess how much inventory to maintain and how often they will need to restock their inventory. Effective demand planning involves mainly (though not exclusively) the use of conventional statistical methods, including linear regression, moving average, and exponential smoothing [13, 14]. While these methods are widely used in demand estimation, they have severe limitations when estimating complex demand patterns and/or when applied to an extremely high volume of data.

Consequently, a more sophisticated approach has emerged — the use of machine learning techniques — which allow companies to forecast future demand using large amounts of data and multiple variable inputs (including macroeconomic conditions) [16, 17]. However, there are still significant challenges associated with using this method, including (but not limited to) the need for an adequate amount and representative dataset (s), data prep/quality issues, and appropriate selection/tuning of algorithms. To overcome these challenges, many researchers recommend using hybrid methods that combine statistical and machine learning forecasting techniques to improve forecasting performance [16, 18]

The effectiveness of replenishment policies relies not only on forecast accuracy but also on the accurate selection and execution of inventory control models. Continuous review systems are suggested for businesses experiencing high levels of variability in their demand profile due to the flexibility they provide in making replenishment decisions. The Implementation of continuous review systems generally requires ongoing monitoring of inventory levels and, in some cases, relies upon advanced technology (e.g., ERP/WMS systems) to support this process. These systems improve decision-making processes; however, for small-to-medium-sized businesses, they may be prohibitively expensive to implement.

Additionally, some previous research suggests that in continuous-review systems, when dealing with standardized items, traditional purchasing criteria (price/quality) may not necessarily be as important in the decision-making process [19]. An alternative approach for limited tech resource systems is to use periodic review policies that require less upfront investment and provide flexibility in adjusting to changing demand patterns (using forecasting methods such as Croston) [20]. In conclusion, successful inventory control involves aligning the method used for predicting demand with the method used for replenishment and should take into account operating conditions as well as all other factors affecting efficient inventory management, including minimizing stockouts and overstocks.

## 3. Methodology

The research is applied, descriptive, and a case study, developed in a commercial company in Peru dedicated to the distribution of products for welding activities. The proposed model intends to test an inventory design that considers the inventory policy and the management of the warehouse. The information was collected based on AppSheet. Additionally, the proposed model considers a data-driven approach through the digitalization of inventory records and automation of decision-support processes. A low-cost digital system is proposed that centralizes inventory information, makes KIP visible to see them in real-time, and generates alerts for replenishment decisions and slow-moving inventories. This combination improves responsiveness and accuracy without sophisticated technology, thus optimizing small and medium-sized enterprises.

The design was broken down into three stages. The first stage consisted of a literature review that sought to identify the main problems of commercial companies, their respective indicators, and the tools they would resort to for warehouse management, inventory policies, and demand forecasting. Onwards, the diagnostic stage involves the analysis of historical KPIs for trend evaluation, classification of the products through an ABC analysis for later, more fine-grained evaluation, and the application of a Value Stream Mapping (VSM) to rate the warehouse management. In this stage, it was possible to calculate indicators such as inventory turnover, logistics costs, inventory record accuracy, and location errors. Finally, the proposed model was validated through a hybrid approach being pilot and a simulation.

### *3.1. Proposed Model*

The proposed model presented in Figure 1 includes the most relevant aspects present in the literature and applies it to the company under study. Considering that the model has two components, the first component is focused on inventory planning and is integrated by a replenishment model that proposes alignment with the real conditions of demand, relieving excess stocks and increasing turnover. As demand analysis revealed a high variability in MAPE, this was the most appropriate alternative for a demand forecasting tool.

In this way, it is proposed to implement a Min–Max inventory policy under continuous review (s, S) where the reorder point is the minimum level (s) and the maximum level (S) results from the addition of the reorder point and the economic order quantity. The second component refers to warehouse management, where tools such as 5S and cycle counting are acquired in order to improve organization, inventory accuracy, and control. Operational data collection and monitoring were made using the AppSheet tool, which allowed the digital recording of all the collected information referring to the warehouse inventory and management, which made it reliable to be used also for the purpose of analysis. This data was considered.

### *3.2. Model Components*

#### *3.2.1. Component 1: Inventory Policy*

The first component of the model focuses on inventory policy, whose purpose is to establish a replenishment model for slow-moving products. Because of the number of items in the company's portfolio, an ABC classification by product families is first applied in order to focus only on the relevant ones. Due to the gap identified at the diagnostic stage of the problem, an inventory turnover of 4.1 times a year is set, making it possible to identify slow-moving products. Given that, a sample of 23 products is selected, which represents around 15% of the company's revenue. Streamline is the software chosen to characterise demand and culminate in the identification of the most suitable forecasting technique. The analysis showed that only two products exhibit continuous demand with an MAPE lower than 30%, and the remaining products have great demand variability; in this case, the average demand is used as an estimation alternative. In a situation of high variability, the Min–Max, continuous review inventory policy (s, S) might be viable, with the reorder point corresponding to the minimum level (s), and S being the maximum level calculated as the summation of the reorder point with the Economic Order Quantity (EOQ); for the model the average demand of 6 months is used. Finally, for the simulation to be validated in Arena, the FSN classification (fast, slow, and non-moving) is determined for inventory behaviour, according to turnover [21].

#### *3.2.2. Component 2: Warehouse Management*

The second component of the model addresses warehouse organization and control through Lean Warehousing tools, especially 5S and cycle counting. The 5S applies to improving order and standardization of the warehouse. The Seiri phase helps to identify non-moving products; Seiton creates rack labelling and a new location coding system to make locating easier; Seiso is to keep workspaces tidy, and Seiketsu brings in that internal audits take place from time to time to measure the sustainability of these improvements. Cycle counting is the Implementation of a periodic inventory control system by means of a schedule of weekly counts, selecting priority products to be counted on the basis of sales level and turnover. This enables discrepancies between physical inventory and recorded inventory to be detected and thus improve confidence in the inventory figures.

Finally, data on operations are entered through AppSheet, resulting in centralising all inventory and warehouse data live, thus monitoring performance indicators, and making decisions. How to combine the two is illustrated in Figure 2, where the structure of the proposed model and the combination of inventory policy and warehouse management appear. The model is intended to demonstrate how data-driven decision-making will, via digital tools and Lean, contribute to a concerted approach to deal with inventory turn and operational efficiency.

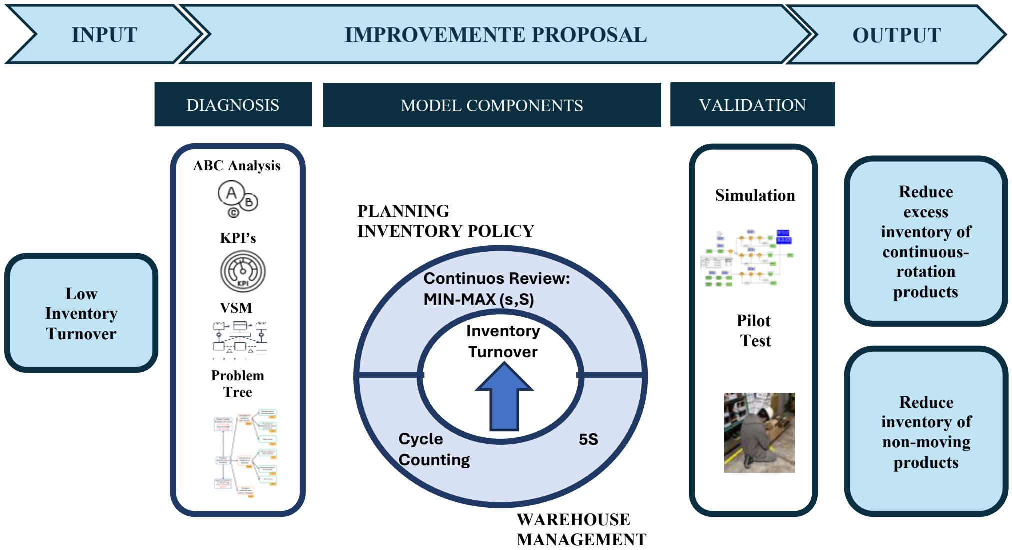


**Fig. 1 Proposed model**

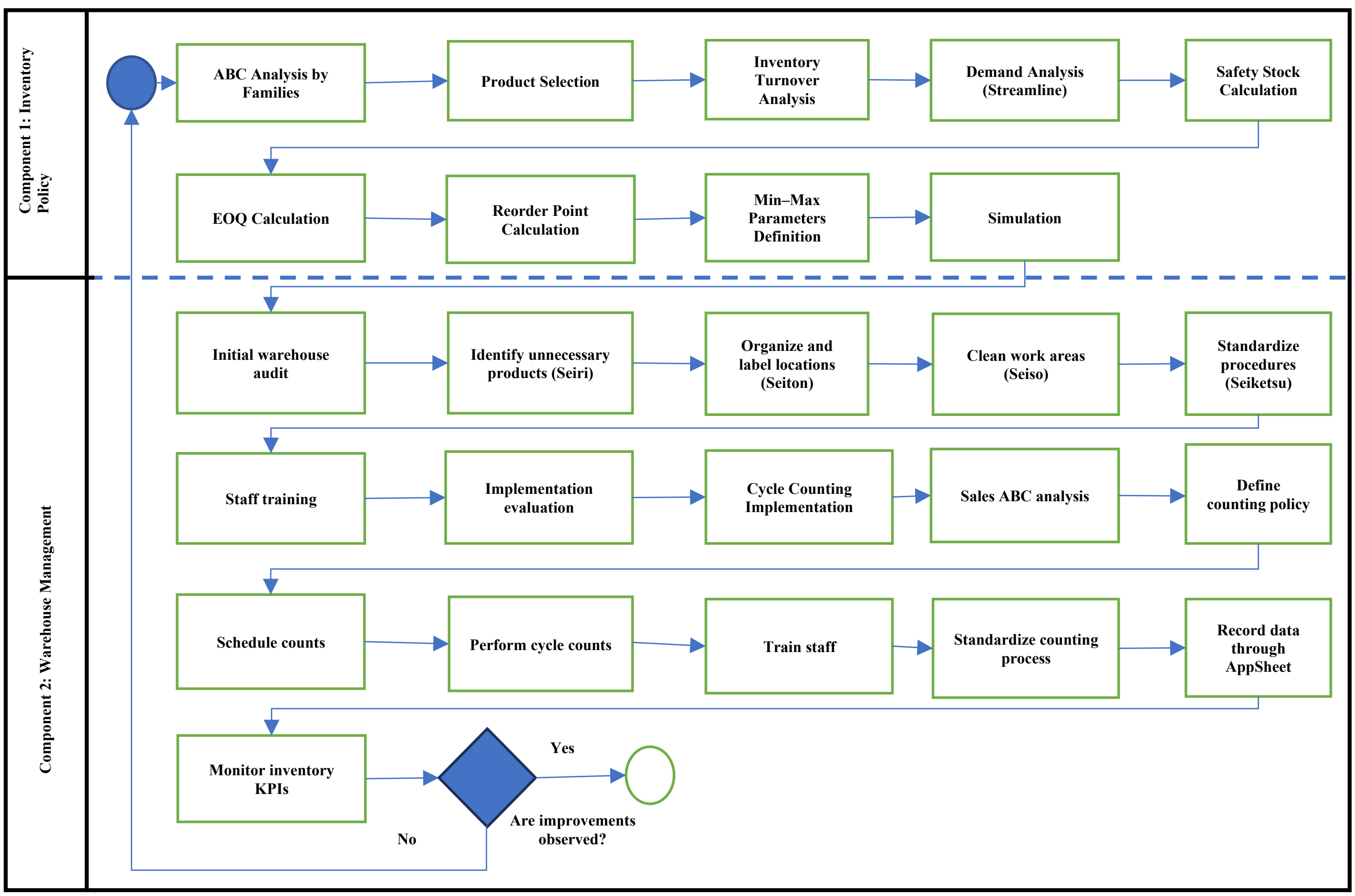


**Fig. 2 Proposed model implementation flow**

### *3.3. Model Indicators*

Inventory Turnover (ROT): It shows how many times a company's inventory is sold and replenished during a given period. According to industry benchmarks, the expected turnover is 3.53.

$$ROT = \frac{\text{Cost of Sales}}{\text{Average Inventory}} \quad (1)$$

Non-Moving Inventory Index: Reflects the accumulation of products with low or no rotation within the inventory. According to studies, the target value is 0% [15].

$$\% = \frac{\text{Non-moving Inventory}}{\text{Average Inventory}} \times 100 \qquad (2)$$

Inventory Record Accuracy (IRA): Measures the degree of agreement between the inventory records in the system and the actual quantities found physically. According to studies, the expected level is 97% [8].

$$IRA = \frac{\text{Total Exact Records}}{\text{Total Records}} \times 100 \qquad (3)$$

Not Located Products (NLP): Measures the proportion of products recorded in the system that cannot be physically located. According to studies, the target value is close to 0% [8].

$$NLP = \frac{\text{Not Located Products}}{\text{Total Inventory}} \times 100 \qquad (4)$$

Logistics Costs: Logistics costs correspond to the sum of ordering costs and inventory holding costs associated with managing inventory. According to studies, the goal is to reduce these costs by 60% [22].

$$\text{Logistics Costs} = \text{Ordering Cost} + \text{Holding Cost} \qquad (5)$$

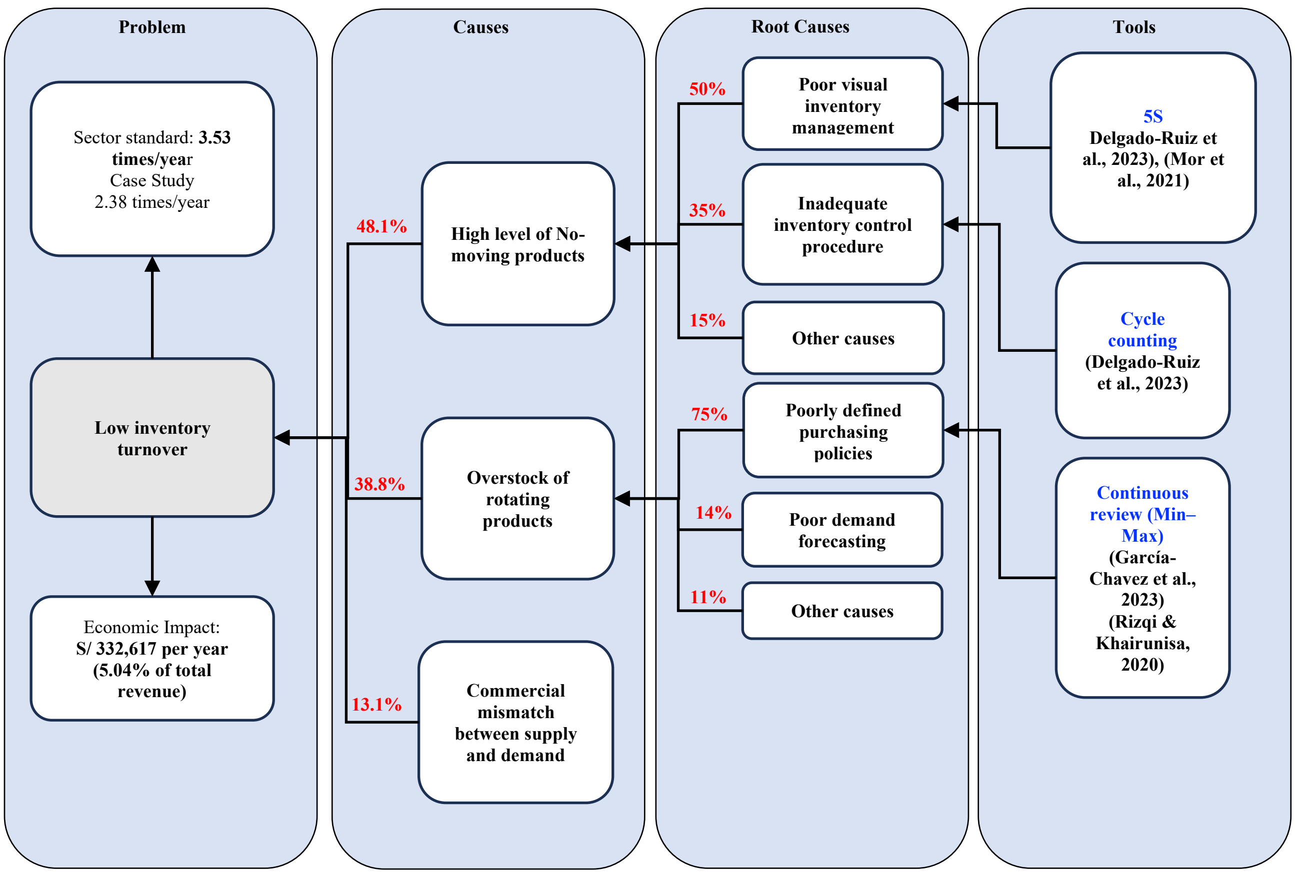

**Fig. 3** Problem tree

## 4. Results and Discussion

### *4.1. Scenario Description*

This section describes the Validation of the Implementation of the improvement model previously described. A detailed report is made on the development of each component is provided, highlighting their integration within the model. Emphasis will be done on the Implementation of the inventory policy based on the MIN-MAX method, as well as the use of Lean Warehousing tools to improve the organization of the warehouse and the application of the 5S methodology and cycle counting. Finally, AppSheet is proposed as the information platform for keeping records and monitoring inventories, and the results obtained from the latter.

### *4.2. Initial Diagnosis*

The company is a trading company, and its main problem is a low turnover rate; its turnover is currently 2.38, while the sector benchmark is 3.53. This results in high logistics costs of 5.04% of revenues, or PEN 332,617 per year. This is mainly due to two main causes: first, excessive immobilized product and the highest inventory holding costs; and second, an excess of inventory for products with no demand; the company is buying more units than they need. The first cause is associated with deficient inventory management, evidenced by an NLP of 45% and a deficient control of their inventory, as shown by an IRA of 86%. High logistics costs and a 40% unsold stock ratio also indicate that there is excess inventory in the system. For a detailed breakdown of the problem, see Figure 3; it starts with the main problem and is gradually broken down to underlying causes until reaching root causes and the set of tools selected to ameliorate them.

### *4.3. Design and Validation Results*

This process deals with the flow from when product purchasing is completed, until the process, but emphasises more on the replenishment activities. The company has a wide product range, from welding consumables to abrasives, industrial markers to PPE, to mention a few. An ABC analysis was carried, and the main relevant family of product concluded from that study was weld consumables, for which a MIN–MAX inventory policy and also use of 5S and cycle counting will help to cut purchases generated from waste, and also idle products in stock.

#### *4.3.1. 5S Implementation*

For the application of the 5S methodology, an area selected at random, populated with welding family products, was chosen. The fundamental use to be made of this tool is classifying and ordering the product, making it clear where items of low movement are, and improving where they are stored. In other words, it aims to decrease NLP (Not Located Products) and help decrease the percentage of immobilized inventory. An initial audit was conducted, which revealed several opportunities for improvement across the five stages of the 5S methodology. The results are presented in Figure 4.

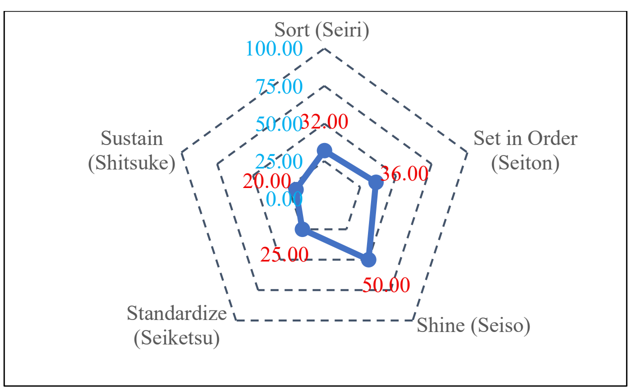


**Fig. 4 Initial audit results**

*Application of the First S – Sort (Seiri)*

The first step consisted of documenting the current warehouse conditions through photographs, which allowed the identification of several improvement opportunities. In addition, the Red Tag strategy was implemented based on the 5 Pillars of the Visual Workplace proposed by Hirano, in order to identify unnecessary products or items requiring special attention and allow prompt corrective action. This tool helps prevent product obsolescence and identify idle inventory that does not add value. Once unnecessary products were identified, a specific area within the warehouse was designated to temporarily store these items and determine the appropriate action to be taken. For this purpose, a layout of the current warehouse situation was developed to determine the most suitable locations for storing the products. Finally, based on the list of items identified with red tags, the corresponding evaluation process was followed to determine the appropriate action for each item.

*Application of the Second S – Set in Order (Seiton)*

This second S focuses on returning each item to its right place. We started with visual flow layouts of the locations in the warehouse on how best to organize them, making for improved classification of products (ex, by brand, weight, turnover, size). This also permitted delimiting of special areas for product bundles, immobilized inventory, and put on hold nearing its expiration.

In conjunction with the warehouse workers, we restructured products according to criteria set by the company, such as weight and rotation. The next step was to label spaces, columns, and products so they could be found easily and quickly. For this, we developed a new location coding system.

Four types of storage space were defined as not separated by aisle: separated pallets (K), Racks (R), grouped pallets (P), and Shelves (S).

To distinguish separate elements located in each storage space, the letters X, Y, and Z were used.

Columns were identified by the followed letter system: A, B, C, D, E; and the rows from the bottom to top, in order, thus: 1, 2, 3, etc.

This simple coding system greatly reduced NLP (Not Located Products) as it made more efficient use of the storage, in addition to assigning locations for other warehouse equipment used, such as carts, ladders, and tools. Proper marking of racks, shelves, and pallets of vehicles helped to prevent product from being left in the aisles or outside of its proper area. The layout design conformed to the Spanish NTP 852 standard recommendations, suggesting at least a meter of space for pedestrian walks.

*Application of the Third S – Shine (Seiso)*

A cleaning plan was developed to maintain optimal warehouse conditions. This plan identifies the responsible personnel, the area to be cleaned, the specific cleaning activities, and the frequency of each task. The document helps ensure systematic cleaning and proper warehouse maintenance.

For example, in the rack and shelving areas, cleaning tasks include the removal of solid residues, inspection for rust or structural deformation, and recording observations such as the need for rust removal or preventive painting.

*Application of the Fourth S – Standardize (Seiketsu)*

At this stage, the documentation required for the 5S Implementation was established, including the plans corresponding to each S, the self-evaluation format, and the design of warehouse labels. Additionally, a 5S visual management board was implemented to maintain continuous monitoring of the process. This board displays updated information on self-evaluations, cleaning plans, and improvement action plans. These updates are conducted quarterly, ensuring continuous monitoring and improvement of workplace conditions.

*Application of the Fifth S – Sustain (Shitsuke)*

Finally, a follow-up plan was established through a schedule of training sessions and periodic self-evaluations to identify errors and improvement opportunities. These activities aim to reinforce discipline and ensure the long-term sustainability of the 5S methodology. A final audit was conducted to evaluate improvements across the five stages after the Implementation of the tool.

*4.3.2. 5S Validation*

After the 5S Implementation, a total score of 82.40% out of 100% was obtained in the final audit, as shown in Figure 5. In addition, the Not Located Products (NLP) indicator was measured four weeks before and four weeks after the pilot implementation, which lasted one month. In each of the weeks indicated, three readings were taken: at the start of the week (Monday), midweek (Wednesday), and the end of the week (Friday), resulting in a total of 12 readings (weeks multiplied by three weekday readings) in the AS-IS case and 12 readings in the TO-BE case. The result is that the NLP indicator dropped from 45% to 0.4%, so that the practical application of the 5S work at the location obviously had a huge impact on the accuracy of the location and product.

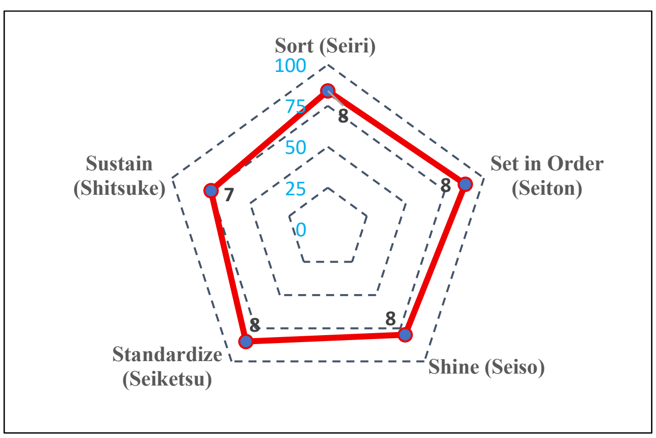


**Fig. 5 Final audit results**

*4.3.3. Cycle Counting Implementation*

For the application of the methods of this tool, it was decided to use the welding product family to configure a system of inventory controls by cycles. As a general premise, the purpose of this tool is to improve the Inventory Record Accuracy (IRA), from where type A items, where discrepancies between what the system shows and what exists arise, become evident. An initial assessment of the indicator showed an IRA of 86%, which exposed the need to strengthen the inventory control mechanisms. Through the Implementation of cycle counting based on ABC classification, and with the minimum frequencies established in the counting schedule, to increase the IRA and trustworthiness of the same.

*Application of Cycle Counting*

Inventory Record Accuracy (IRA), as another inventory rotation Key Performance Indicator (KPI), points out that when a product is supposedly available in the inventory but cannot be easily located in the warehouse, it leads to information mismatch that can eventually create immobilized inventory. Indeed, cycle counting was chosen as the control methodology to help harden inventory accuracy.

A control methodology, the US Government Accountability Office guide Best Practices in Achieving Consistent, Accurate Physical Counts of Inventory and Related Property, and ASTM E2132-17 were used as the basis to create an ABC sales analysis across all products within the welding family that are maintained in the warehouse. This information was used to determine the frequency of counting for each product family, effectively determining the counting schedule.

Based on the analysis, there were found to be 65 products SKUs in category A, 198 in category B and 395 in category C. Because of the size of category A, representing 81% of total sales, the firm scheduled monthly counting of those Stock-Keeping Units (SKUs) three times during a month, followed by those in categories B and C, with two counts in B and one count in C currently scheduled. The warehouse operator physically counts the stock and makes observations during counting, again following a schedule that covers a 22-day counting cycle.

The firm developed standardized formats to enable them to take blind counts in a standardized manner across the entire product line, again following established principles, but decided to use an internet-based application to actually enter information related to counts to facilitate data computation. The web-based application, developed in AppSheet, is shown in Figure 6. In turn, the application allows the user to enter information such as the date of count, product ID, and three independent counts of product (s). The application automatically calculates the average of the counts and compares it with the stock of record in the system to produce the proper discrepancy. Actual IRA is also automatically calculated in the AppSheet application, facilitating continual watching, and if problems are detected, the operation can respond.

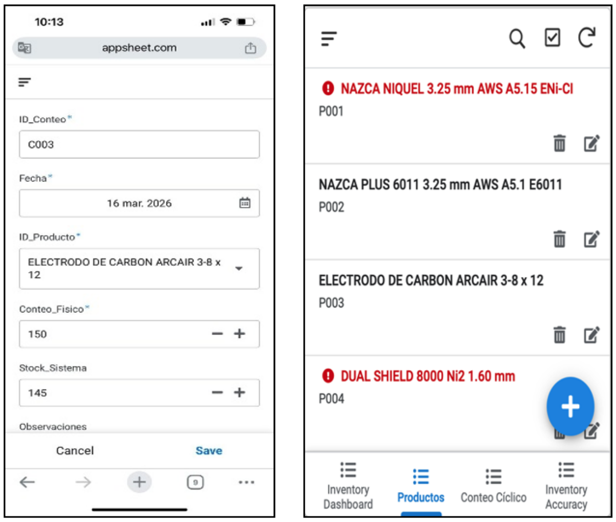


**Fig. 6 AppSheet-based interface for inventory data registration and real-time monitoring**

*4.3.4. Cycle Counting Validation*

To carry out the cycle counts, the team was organized so that each count was performed at least three times. This approach aimed to minimize counting errors and obtain more accurate results. For the calculation of the Inventory Record Accuracy (IRA) indicator, the measurements were taken during the same period used for the Not Located Products (NLP) data collection: four weeks before the Implementation and four weeks after the Implementation. During this period, three counts were conducted per week, resulting in 12 measurements in the AS-IS scenario and 12 measurements in the TO-BE scenario. As a result, the IRA increased from 86% to 95%, demonstrating an improvement in inventory record accuracy after the Implementation of cycle counting. A statistical validation of the results confirmed the consistency of the observed improvements before and after Implementation, supporting the reliability of the measured changes in inventory accuracy.

*4.3.5. Min-Max Implementation*

First, an ABC classification by product families was performed in order to identify those with the greatest relevance in the company's sales. The results showed that the welding product family accounted for approximately 75% of total sales, and therefore, it was selected for further analysis.

Subsequently, an inventory turnover analysis was carried out at the product level within this family. Based on this analysis, products with low turnover and significant participation in inventory were identified. As a result, 23 products were selected for the development of the model.Once the list of products was defined, the Streamline forecasting software (Figure 7) was used to determine the best available forecasting method and an appropriate inventory replenishment model. During this process, the forecast accuracy was evaluated using the MAPE indicator for each product. The results showed that only one item had an MAPE below 30%, indicating an acceptable level of forecasting accuracy. For the remaining products, a high variability in MAPE values was observed, making the average demand the most recurrent and appropriate alternative in these cases.

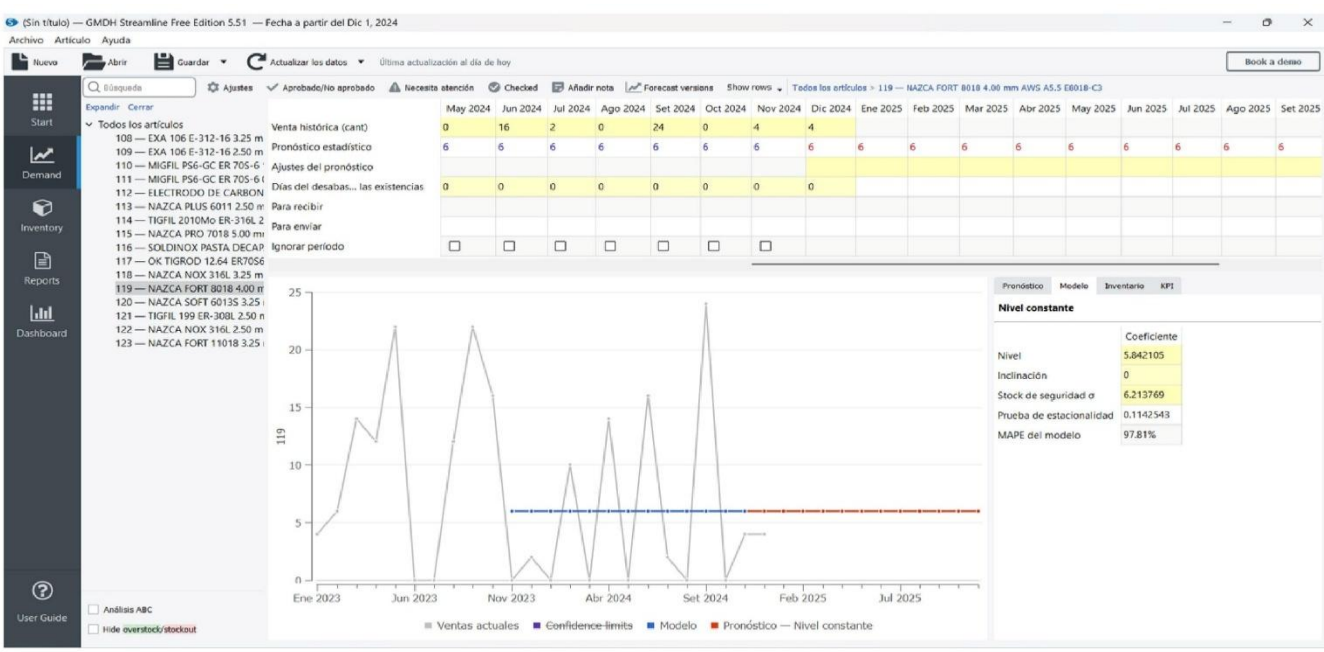


**Fig. 7 Demand forecasting and MAPE evaluation using streamline software**

Considering the high variability in demand, a Min-Max inventory policy with continuous review (s, S) was proposed. In order to reduce the variability of the data used in the calculations, the last six months of demand were considered to estimate the average monthly demand for each product. The first step was to calculate the minimum inventory level (s) using the reorder point formula, where d represents daily demand, L is the supplier lead time, and SS is the Safety stock.

$$s = d * L + SS \qquad (6)$$

For the calculation of safety stock, a 95% service level and the standard deviation of demand were considered. Regarding the lead time, a value of three days was assumed since all products are supplied by the same local supplier. The reorder point was calculated for each product and represents the minimum inventory level. When inventory reaches this level, an alert is triggered to place a purchase order. The order quantity was then determined using the Economic Order Quantity (EOQ) model. According to the dictionary of the Association for Supply Chain Management, the EOQ formula includes annual demand, ordering cost, and holding cost. The EOQ formula used was Equation 7, where D represents the annual demand, K the ordering cost, and h the holding cost.

$$EOQ = \sqrt{\frac{2*D*K}{h}} \qquad (7)$$

In this study, an ordering cost of PEN 219.00 was considered, while the holding cost varies depending on the product.

The maximum inventory level (S) was calculated as the sum of the reorder point and the EOQ. Once the minimum and maximum inventory levels were determined, the average inventory level was calculated using the following Equation 7 for average inventory.

$$Average\ Inventory = s + (S - s)/2 \qquad (8)$$

Through this process, the new average inventory levels were obtained for each of the analyzed products. These parameters will be incorporated into a simulation developed in Arena Simulation Software in order to evaluate the performance of the proposed inventory system. Additionally, an application was developed using AppSheet (Figure 8, which served as a support tool for managing the proposed model. The application allows the automatic calculation of the minimum and maximum inventory levels, EOQ, and current stock levels by entering the product ID and parameters such as ordering cost, demand from the last six months, holding cost, and safety stock. Inventory movements (inbound, outbound, transfers) on AppSheet are managed through a central repository connected to Google Sheets. The system automatically updates important fields like lot status, available quantity, and current location. In addition, the app dashboard provides visual alerts when a product reaches its reorder point so that appropriate actions can be made with respect to inventory replenishment. The purchase recommendation table serves this function and highlights in red the products requiring replenishment. The app, therefore, proves useful as an operational support tool for the tactical Implementation of the proposed inventory policy.

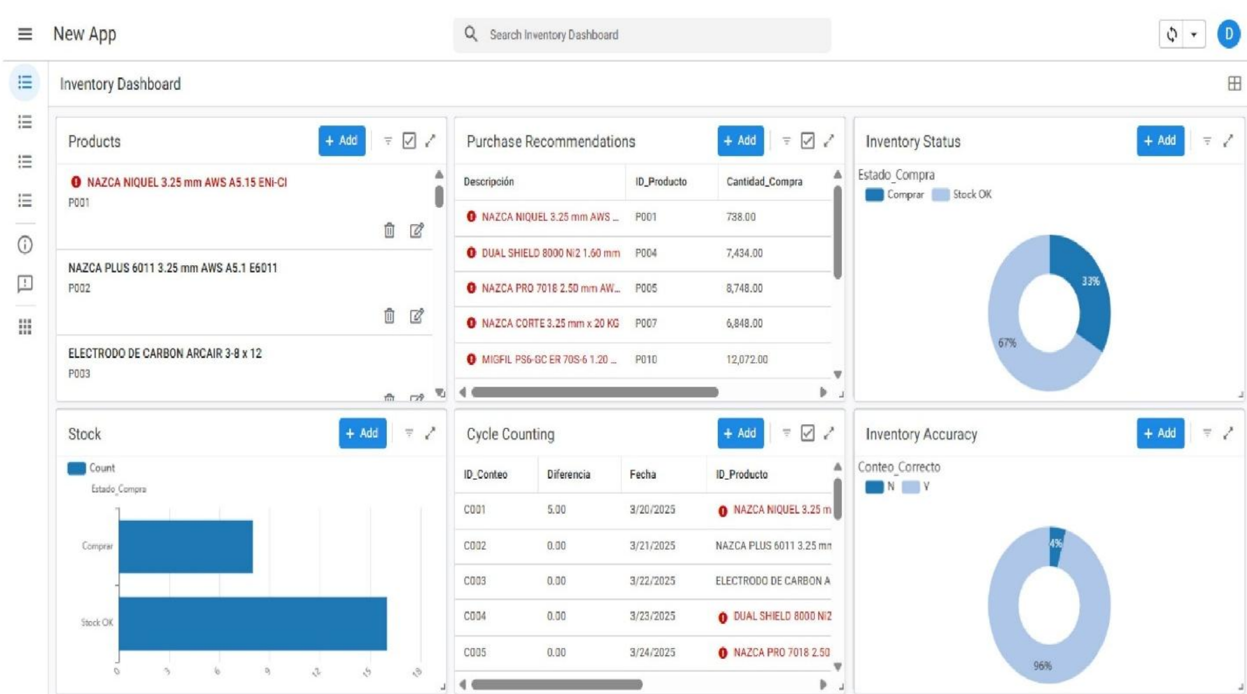


**Fig. 8 AppSheet dashboard for real-time inventory monitoring and decision support**


**Fig. 9 Automated alert notification for immobilized inventory generated by the data-driven system**

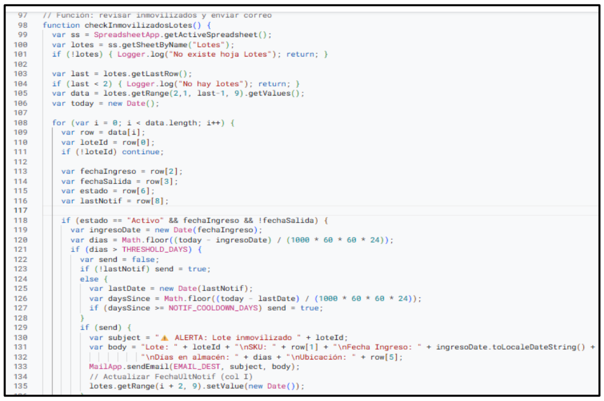

**Fig. 10 Google apps script code for automated inventory monitoring and alert generation**

To facilitate inventory monitoring, firm-wide processes were enabled utilizing event-driven scripting; that is, scripts that are automated to execute through schedule-driven triggers against certain changed states in the system. These scripts effectively "look" at aged inventory to identify lots exceeding a certain period of inactivity, such as being on hand with more than 60 days of inactivity, and, if [condition] is true, trigger email alerts that are sent to the warehouse manager at certain intervals (e.g., every seven days until action is taken). This alert function is useful for facilities to conduct early proactive analysis of inventory and make decisions regarding slow-moving or aging inventory. Figure 9 shows the alert email sent to the warehouse manager, and Figure 10 shows the script used to drive the execution of the automated notifications.

### *4.3.6. Model Simulation in Arena*

In simulating the Min–Max inventory policy, three products were selected based on turnover levels as representative items since simulating the full population would have been unwieldy, i.e., the order quantities, average inventory, lot size purchased, and demand patterns differ significantly from one another. A grouping or stratification approach was then adopted, and one representative item was selected for each. Selection was made using purposive sampling (expert judgment).

The selected items belonged to the turnover level with the largest number of orders or volume sold, and their characteristics were otherwise similar, which allowed them to present typical inventory behavior and facilitate the comparison between the current ("As Is") and proposed ("To Be") state versions of the problem. The three products selected were the following: Nazca Pro-7018 3.25 mm - the highest number of orders in 2024; Nazca Nickel 3.25 mm - highest sales value, PEN 187,596.43; and Dupla Shield II 70 Ultra 1.60 mm, high immobilized inventory (PEN 6,233.67). Data acquired were the average inventory, the size of the purchase lot, and demand from the three warehouses of the company to simulate the complete system.

**Table 1. Product category**

| Category | Description |
|---|---|
| A | Products exceeding the turnover threshold of 4.1 |
| B | Products below the turnover threshold of 4.1 but with recorded sales |
| C | Fully immobilized products due to disorganization |

The simulation process starts with the collection of relevant data, i.e., demand, interarrival times between orders, order quantities, purchase lot size, current probability of a sales item not being located at assigned stocks, probability of matching physical and system inventory records, average inventory, and ordering and holding costs in the company. The data relating to IRA and NLP were collected from the pilot test and AppSheet. For interarrival times, appropriate statistical distributions were assigned. Based on these inputs, the current scenario ("As-Is") was modeled and simulated. The outputs included final inventory levels (in units and monetary value), incorrect records, misplaced items, purchase quantities, number of orders placed, and ordering and holding costs. Subsequently, new input data were defined based on the Implementation of 5S (updated location accuracy), cycle counting (updated inventory accuracy), and the Min–Max inventory policy (average inventory, purchase lot size, and minimum and maximum inventory levels). Using these updated parameters, the proposed scenario ("To-Be") was simulated. Finally, the results of both scenarios were compared. Table 2 summarizes the input parameters used in the simulation model for the As-Is scenario. Figure 11 shows the results obtained from the Output Analyzer of the As-Is model.

**Table 2. Distributions of the input parameters AS-IS**

| Input Parameter | Distribution |
|---|---|
| Interarrival time of orders | Expo (2.26) |
| Demand size 1 | Disc (0.65, U (1,50); 0.84, U (51,150); 0.93, U (151,400); 0.98, U (401,700); 1, U |

| | |
|---|---|
| | (701,1800)) |
| Demand size 2 | Disc (0.77, U (1,10); 0.89, U (11,20); 1, U (21,50)) |
| Demand size 3 | Disc (0.71, U (1,100); 0.85, U (101,200); 1, U (201,300)) |
| Purchase lot size 1 | U (500,2000) |
| Purchase lot size 2 | U (50,100) |
| Average inventory 1 | 2482 |
| Average inventory 2 | 136 |
| Average inventory 3 | 300 |
| NLP | 86% |
| IRA | 45% overall (0%, 36%, 100% by group) |

OUTPUTS

| Identifier | Average | Half-width | Minimum | Maximum | # Replications |
|---|---|---|---|---|---|
| Compras NazcaPro | 8.0000 | .00000 | 8.0000 | 8.0000 | 120 |
| Costo Almac NazcaNi | 15046. | 355.61 | 9996.0 | 19362. | 120 |
| Ubic Incorrec NazcaNi | 3.9583 | .33582 | .00000 | 10.000 | 120 |
| Costo Pedir NazcaNi | 868.00 | .00000 | 868.00 | 868.00 | 120 |
| Inv en Soles NazcaNi | 1.1519E+5 | 2722.4 | 76526. | 1.4823E+5 | 120 |
| Reg Incorrec Dual | .67500 | .15215 | .00000 | 3.0000 | 120 |
| Inv en Soles Dual | 6234.0 | .00000 | 6234.0 | 6234.0 | 120 |
| Costo Pedir NazcaPro | 1736.0 | .00000 | 1736.0 | 1736.0 | 120 |
| Costo Almac NazcaPro | 10184. | 541.14 | 3676.3 | 16402. | 120 |
| Stock final Dual | 300.00 | .00000 | 300.00 | 300.00 | 120 |
| Unid_Compr NazcaNi | 294.65 | 5.2523 | 233.00 | 377.00 | 120 |
| Inv en Soles NazcaPro | 78225. | 4156.6 | 28238. | 1.2599E+5 | 120 |
| Reg Incorrec NazcaPro | 7.0583 | .49113 | 1.0000 | 14.000 | 120 |
| Unid_Compr NazcaPro | 10153. | 220.73 | 6968.0 | 12901. | 120 |
| Stock final NazcaNi | 358.25 | 8.4669 | 238.00 | 461.00 | 120 |
| Compras NazcaNi | 4.0000 | .00000 | 4.0000 | 4.0000 | 120 |
| Ubic Incorrec Dual | 4.1500 | .40562 | 1.0000 | 11.000 | 120 |
| Ubic Incorrec NazcaPro | .00000 | .00000 | .00000 | .00000 | 120 |
| Stock final NazcaPro | 7379.8 | 392.13 | 2664.0 | 11886. | 120 |
| Reg Incorrec NazcaNi | 1.8166 | .25560 | .00000 | 6.0000 | 120 |
| orden.NumberIn | 71.550 | 1.5482 | 51.000 | 93.000 | 120 |
| orden.NumberOut | 71.550 | 1.5482 | 51.000 | 93.000 | 120 |
| control1.NumberIn | 8.0000 | .00000 | 8.0000 | 8.0000 | 120 |
| control1.NumberOut | 8.0000 | .00000 | 8.0000 | 8.0000 | 120 |
| control2.NumberIn | 4.0000 | .00000 | 4.0000 | 4.0000 | 120 |
| control2.NumberOut | 4.0000 | .00000 | 4.0000 | 4.0000 | 120 |
| control.NumberIn | .00000 | .00000 | .00000 | .00000 | 120 |
| control.NumberOut | .00000 | .00000 | .00000 | .00000 | 120 |
| NazcaPro.NumberSeized | 5255.8 | 275.94 | 2288.0 | 9791.0 | 120 |
| NazcaPro.ScheduledUtilization | .37918 | .02538 | .13453 | .78322 | 120 |
| Dual.NumberSeized | .00000 | .00000 | .00000 | .00000 | 120 |
| Dual.ScheduledUtilization | .00000 | .00000 | .00000 | .00000 | 120 |
| NazcaNi.NumberSeized | 72.408 | 6.8002 | 9.0000 | 185.00 | 120 |
| NazcaNi.ScheduledUtilization | .14927 | .01479 | .01003 | .43963 | 120 |
| System.NumberOut | 83.550 | 1.5482 | 63.000 | 105.00 | 120 |

**Fig. 11 Simulation results and confidence interval analysis obtained from the arena output analyzer (As-Is Scenario)**

### *4.3.7. Model Validation*

In the To-Be model, data were collected from warehouse pilot tests, in particular, inventory accuracy and location errors. These parameters were incorporated in the model, with enhanced percentages. An inventory policy based on a Min–Max model was executed. In this model, the minimum inventory level is the reorder level, the point where a purchase order is required. The order quantity was revised as well, using the Economic Order Quantity (EOQ). The maximum inventory level was defined as the reorder point plus the EOQ. The input parameters that were used for the simulation model are shown in Table 3. The To-Be model proceeds in a like manner to the As-Is. Orders arrive in sizes that reflect the typical order sizes seen at the company, as client order sizes vary. The IRA indicator (Inventory Record Accuracy) determines whether the system shows that the order can indeed be filled. The IRA revealed itself to be some 95% following implementation of the cyclic counting policy, and this statement was substantiated through warehouse pilot tests. The next decision is about what is currently available. The Reorder Points (ROP) for product 1, a relatively compact item, and for a second-generation product, fragile and awkward. When inventory on hand reaches an ROP of 212 kg for product 1 and 30 kg for product 2, an order should be generated.

The presumably correct number of orders placed should be based on Economic Order Quantities (EOQ) of about 1,926 kg for our first item and 74 for item two. Finally, knowledge of an improved type of ERU is plugged in (the location error rate). The pilot test performed in the warehouse as a 5S application called for the sort and removal of the S. In the S (As Is) in the 5S flair, obsolete products falling out of touch with production, having also seen no sales over what could be termed many years, were discovered in the S (Set in Order) phases of the S (See)_2nd stage in the S (Set-in-Order) cycle. The setting in order dealt with labeling (including organization and management). The end result here will be an upswing in numbers closer to zero all around: worker team, 006,006,051% at the group level. Figure 12 reveals that the simulation models produced results, leading to the development of a final simulation model using Arena.

**Table 3. Distributions of the input parameters To-Be**

| Input Parameter | Distribution |
|---|---|
| Interarrival time of orders | Expo (2.26) |
| Demand size 1 | Disc (0.65, U (1,50); 0.84, U (51,150); 0.93, U (151,400); 0.98, U (401,700); 1, U (701,1800)) |
| Demand size 2 | Disc (0.77, U (1,10); 0.89, U (11,20); 1, U (21,50)) |
| Demand size 3 | Disc (0.71, U (1,100); 0.85, U (101,200); 1, U (201,300)) |
| EOQ 1 | 1926 |
| EOQ 2 | 74 |
| Average inventory 1 | 1175 |
| Average inventory 2 | 67 |
| Average inventory 3 | 300 |
| Reorder point 1 | 212 |
| Reorder point 2 | 30 |
| NLP | 95% |
| IRA | 0% overall (0%, 1%, 0% by group) |

To determine the number of simulation replications, the As-Is model was initially run with 30 replications. Based on the results obtained, the performance indicator with the highest half-width was identified, as reducing this value increases the precision of the model. The required number of replications was calculated using Equation X, where $N$ is the optimal number of replications, $N_0$ is the initial number of replications (30), $h_0$ is the initial half-width (8602.9), and $h$ is the desired half-width, defined as 50% of $h_0$ (4301.45).

$$N = N_0 \times (h_0^2 / h^2) \tag{8}$$

Applying this formula resulted in 120 required replications. The As-Is model was then run using this number to verify the half-width condition. The resulting half-width was 4156.6, which is lower than the proposed value (4301.45), confirming that the model with 120 replications meets the desired precision level.

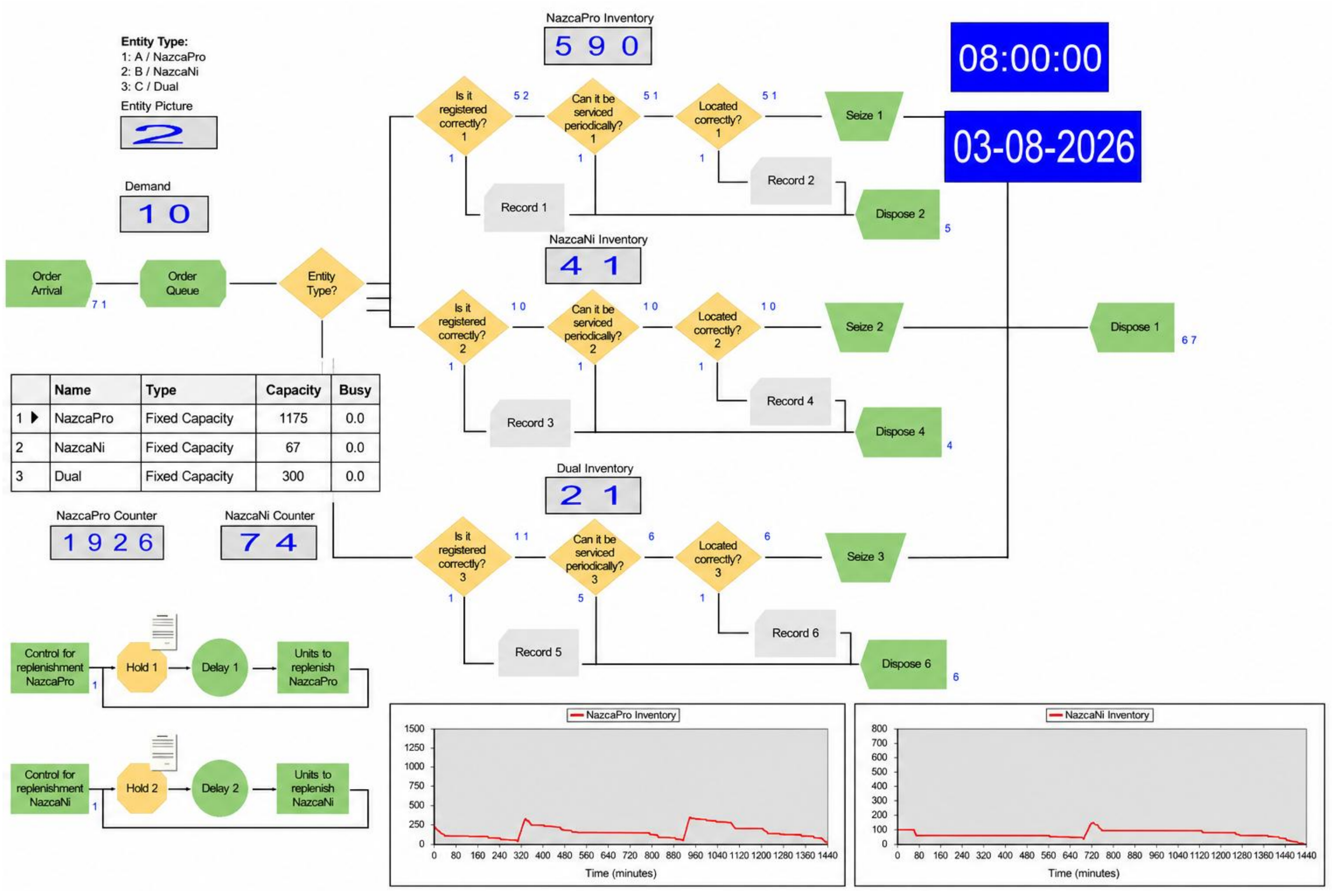


**Fig. 12 Arena simulation model for the evaluation of the proposed inventory system (To-Be Scenario)**

*4.3.8. Results*

Confidence intervals for these results were calculated using the Output Analyzer after running the simulation model with 120 replications (based on their corresponding averages and half-widths). In the As-Is, where inventory policy is being followed, the final stock level of Nazca Nickel (a product representing the group with inventory turns below 4.1) was estimated between 349.78 kg and 366.72 kg. In contrast, in the To-Be model, a MIN–MAX policy was used to prevent overstocking, giving rise to a much lower level of stock, ranging from 61.15 kg to 69.62 kg. This is a significant drop, leading to considerable gains in lower holding costs. Ordering costs are also lower. Purchase orders for Nazca Nickel have fallen from four to two, while the total quantity bought in the period under review has gone from an interval of 289.4–300 kg to 104–121 kg. Graphical comparison of logistics costs, at the 95 percent confidence interval level, is illustrated in Figure 13 and Figure 14. Holding costs are shown in Figure 13 and ordering costs in Figure 14 Indicating differences between As-Is and To-Be.

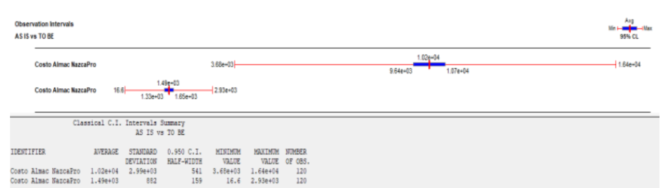


**Fig. 13 Comparison of holding costs for nazca pro between as-is and to-be scenarios with 95% confidence intervals**

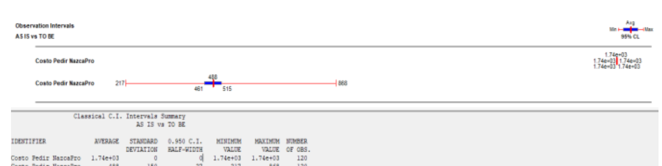


**Fig. 14 Comparison of ordering costs for nazca pro between as-is and to-be scenarios with 95% confidence intervals**

At a 95% confidence level, there is a statistically significant difference in logistics costs. The holding cost of *Nazca Pro* decreased from [9640, 10700] soles to [1330, 1650] soles after implementing the proposed tools. Similarly, the ordering cost showed a significant reduction, decreasing from 1740 soles to [461, 515] soles. Finally, as shown in Table 4, after incorporating the data for *Nazca Ni* (representative of slow-moving items), it can be observed that the Implementation of a Min–Max policy—where the reorder point is set as the minimum inventory level and the maximum level is defined as this value plus the economic order quantity—significantly reduced logistics overcosts by 82%.

**Table 4. Logistics costs**

| Product | Group | Logistics Costs As-Is | Logistics Costs to Be | % |
|---|---|---|---|---|
| **NAZCA PRO-7018** | A | 11920 | 1981 | 83.00% |
| **NAZCA NIQUEL** | B | 15914 | 3076.92 | 81.00% |
| **Total** | | | | **82%** |

On the other hand, for the group of immobilized inventory—represented by the product "Dual"—improvements were observed in location errors. In the As-Is model, between four and five orders were lost due to misplacement. However, after the Implementation of 5S, this value was reduced to zero. Figure 15 presents the comparison of immobilized inventory levels between the As-Is and To-Be scenarios, including the corresponding 95% confidence intervals.

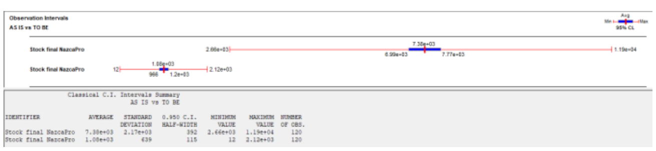


**Fig. 15 Simulation-based comparison of immobilized inventory levels with 95% confidence intervals (As-Is vs. To-Be)**

At a 95% confidence level, there is a statistically significant difference in the final stock of the *Dual* product, which decreased from 300 units to an interval of [60.2, 83.7] units after implementing the proposed tools. Within Group C (non-moving items), changes in final stock levels are also evident. In the AS-IS model, due to warehouse disorganization and inaccurate inventory records, these products showed no movement. However, after implementing 5S and cycle counting, inventory visibility and control improved, reducing this condition and enabling product movement. As a result, the stock level decreased from 300 kg to an average of 71.93 kg.

### *4.4. Discussion*

The use of engineering tools had a significant influence on the turnover of inventory and on the performance of the company. This aligns with previous studies combining inventory classification, demand forecasting, and control models. Prior studies that combined ABC classification, forecasting, and Reorder point and Economic Order Quantity (EOQ) tools jointly reported total inventory reductions of 48% and up to 85% in category A products and an 82% reduction in logistics costs [19]. Compared with those results, our results confirm that the overlay of models also has an effect on inventory levels and operational costs, and that this is more possible to achieve in small and medium-sized firms with reduced resources.

In this regard, structured replenishment policies, or what some authors refer to as pull practices, have yielded effective results with a Min–Max effect. Past studies have reported a reduction of 66.4% in logistics costs and a reduction of 42% in inventory level using a Min–Max with a few complementary tools, [23]. In the same way, the EOQ/reorder point model was able to eliminate excess inventory without decreasing inventory service levels with a logistics cost reduction of 30.66% [13]. Compared with that result, the 82% reduction from the warehouse knowledge results suggests the effect was greater due to the overlapping application of replenishment policies upon the warehouse management practices than simple isolated applications. In environments with year-on-year demands with great variability, indeed, the choice of Inventory policies and their Implementation becomes critical. Substantial cost reductions are present from past studies using a periodic review system; integrated ABC–VED–EOQ approaches were reported [22, 24], and improving inventory efficiency using a hybrid method ABC classification with a Croston model for intermittent demand was used to mitigate holdovers and lost sales [20]. This reinforces the ideas discussed above of coupling inventory policies to the demand environment; in this study, the average stock per month under volatility yields satisfactory results and fortifies a salient decision-rule for the SME, imploring departmental change. The warehouse management and inventory accuracy results also highlight Lean tools improving itself. The Implementation of 5S and cycle counting can obtain a 76% reduction in immobilized inventory by enhancing the location and accuracy of inventory records. Similar improves with poke-yokes and foolproof striving lead to improvements in reductions of obsolete inventories and improving operational efficiency [8, 9, 15]. Ultimately, improving the data accuracy within the organization of the warehouse itself there is beneficial effect, with most likely distant ramifications on improving inventory reliability and decreasing the lack of faith maintenance when making Replenishment-style decisions.

### *4.5. Limitations*

Financial limitations represent an important restriction when it comes to the application of Industry 4.0 technical advances and technologies, which positively impact the making of faster and better decisions and improve inventory management. A potential improvement could come with the

Implementation of RFID technology with an integration in AppSheet, automating data capture. In this case, each lot's inventory would receive a passive RFID tag with a unique EPC code associated with the digital record. RFID readers at every control point would automatically read them every time they arrive at the entry gate, for example, and forward this information to the system using a connected interface or API.

The Implementation in only one of the three warehouses limits the transferability and reliability of the global findings. Another is the random behavior of the demand in the sector that challenged the use of more sophisticated forecast approaches or the use of more complex models; there was not enough data to justify the usage of more complicated models. Finally, the requirement of a reduced set of products to build the simulation model represents a weakness, in this case, given that a wide variety of items is managed by the company, each one featuring different average inventory levels, turnover rates, costs, and more. So, a more powerful simulation framework consisting of the incorporation of a greater range of products and variables is necessary for more comprehensive and generalizable findings.

## 5. Conclusion

The results of this research showed that low inventory turnover in commercial SMEs can be managed by adopting Lean Warehousing practices, inventory policies, and the digitalization of decision-making. The combined model integrates operational tools such as 5S and cycle counting, a Min–Max inventory policy under continuous revision, and the systematization and digital control of inventory data. Logistics costs decreased by 82%. Immobilized inventory went down 76%, while the Enterprise Resource Planning (ERP) accuracy index founded on inventory record precision increased from 86% to 95%. Not located products fell from 45% of the inventory to 0.4%. From a practical nature, the results demonstrate that data systematization and real-time monitoring, combined with systematic and planned decision-making, can substantially improve SME ancillary firm operations without disrupting current practices while increasing control of operations even under low-budget conditions without advanced state-of-the-art technology access, reflecting communion where previously there was dissociation.

The alternative method is low-cost, scalable, and builds on current integral control capabilities and efficient and controlled inventory viewability. The main contribution of this research lies in the development and Validation of an integrated and data-driven model that connects operational practices with inventory planning through accessible digital solutions. This approach addresses an identified gap in the literature and provides a practical framework that can be replicated in similar commercial environments characterized by demand variability and resource constraints. However, this study is limited to a single case study, which may restrict the generalizability of the results. Future research should evaluate the application of the proposed model in different industrial contexts and explore the integration of more advanced forecasting techniques and digital technologies to further improve inventory decision-making and operational performance.

## Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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