# Synergy between SLP, temporal predictive analytics, Industry 4.0 enablers, and fuzzy ABC classification for the systemic improvement of inventory turnover in telecommunications companies.

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***Abstract*– The study analyzes a Peruvian company in the telecommunications sector with a low inventory turnover rate (7.48 vs. 9.2 industry average), mainly caused by incorrect inventory records, inaccurate demand forecasting, inefficient picking processes, and poor product classification. To mitigate these problems, the proposal integrates process standardization and Industry 4.0 tools, along with time series forecasting to improve demand planning, the Systematic Layout Planning (SLP) method to optimize warehouse design, and a fuzzy logic–based ABC model to enhance inventory classification and management, aiming to optimize inventory performance and increase turnover.***

***Keywords*-- Inventory turnover, Industry 4.0, Time series forecasting, SLP, Fuzzy ABC model.***

## I. Introduction

In the global context, the telecommunications sector has consolidated itself as one of the main drivers of digital transformation and economic growth. The expansion of 5G networks, the Internet of Things (IoT), and artificial intelligence have fueled sustained growth in the demand for digital infrastructure and services. Additionally, this industry is composed of companies that provide infrastructure, hardware, and telecommunications services, which are highly relevant due to the volume of revenue it generates, which is expected to grow by approximately 6.14% annually, increasing from USD 2.46 trillion in 2025 to USD 4.21 trillion by 2034 [1].

Internationally, several economies have positioned themselves as leaders in telecommunications infrastructure thanks to accelerated technological deployment and high investment levels in digital connectivity. Among them are China, the United States, South Korea, Japan, and various Western European countries, all of which lead the development of 5G and fiber-optic networks, strengthening their influence in the global market.

At the regional level, Peru stands out in Latin America due to the dynamism of its fiber-optic market, which is considered the fastest-growing in the region, with a projected compound rate of 95.2% over ten years. The country is also part of the "penetration race" for fiber compared to other Latin American economies, reflecting significant progress in network infrastructure and a competitive position in the adoption of next-generation connectivity technologies [2], [3], [4]. Peru also stands out for having more than 41 million active mobile lines, driving an e-commerce sector that represents nearly 5% of national GDP, and generating a broad societal impact by improving access to education, healthcare, and employment strengthening national inclusion and competitiveness [5], [6], [7].

Economically, the telecommunications sector plays an increasingly important role within Peru's productive structure. Characterized by high levels of investment in digital infrastructure and services, the sector contributed 0.11 percentage points to national GDP growth in 2024, demonstrating its economic significance. Total investments reached S/ 4,097 million, representing a 3.4% increase compared to the previous year and an investment-to-revenue ratio of 19.4% [8], [9].

However, in recent years there has been a significant increase in the time technological products remain in storage, aggravating the effects of rapid obsolescence since their value is closely tied to the passage of time. This progressive loss of value turns inventory into an increasingly unprofitable asset, generating immobilized capital and directly affecting business profitability. This situation represents a major financial risk and highlights the need to adopt more efficient inventory management strategies to prevent greater economic impacts. The magnitude of this problem is reflected in its direct impact on the financial and operational stability of technology and telecommunications companies [10], [11]. It not only reduces revenue but also limits their ability to reinvest and grow due to the immobilization of capital in inventories that lose value over time [11], [12]. This effect is amplified in technological products, whose short life cycles and rapid depreciation generate significant losses when they remain in storage for extended periods [13].

Among the factors contributing to this situation are product registration errors, inaccurate demand estimates, delays in product retrieval and placement within the warehouse, and items with low turnover rates [14]. Together, these causes reveal inefficient inventory management, linked to poorly planned purchasing activities and an excess of immobilized products, directly affecting liquidity and profitability. In this context, adopting more rigorous planning strategies and control policies becomes essential to optimize inventory flow and reduce economic loss.

To address the issue of low inventory turnover, the implementation of a management model integrating multiple tools aimed at improving operational efficiency and reducing immobilized capital is proposed [15]. Through process standardization and Industry 4.0 enablers, it is possible to reduce inventory recording errors and strengthen internal control mechanisms [16]. Additionally, the use of Time Series analysis allows for more accurate demand forecasting, enabling better alignment of purchasing decisions with real needs and preventing unnecessary stock accumulation [19].

Furthermore, the incorporation of SLP helps optimize internal layout and significantly reduce picking times, while the combination of ABC classification with Fuzzy Logic enables a strategic categorization of products and a more precise quantification of low-turnover items, allowing for more effective decision-making in their management [17].

Given the above, the integration of these tools is proposed as a comprehensive management model to increase inventory turnover in the company under study. The main motivation behind this proposal is to offer practical and effective solutions that improve inventory management, reduce excess stock, and strengthen the organization's competitiveness, while also serving as a foundation for future research and applications in the sector.

This article is divided into five sections in addition to the introduction. First, Section 2 presents the literature review. Subsequently, Section 3 focuses on the specific research contribution. Section 4 then details the methodology used to validate the results. Section 5 discusses and analyzes the outcomes obtained after implementing the model, and finally, Section 6 provides the study's conclusions.

## II. State Of The Art

To develop the State of the Art, an extensive review of scientific studies related to inventory management in technological and telecommunications sectors was conducted, with the aim of identifying the most effective tools to address low inventory turnover. This search applied quality criteria such as journal quartile ranking, publication recency, and the relevance of each study's contribution. The review enabled the literature to be organized into typologies that both explain the origins of the problem and support the tools that will be integrated into the improvement proposal.

### A. *Low Inventory Turnover*

Inventory turnover is a key indicator for evaluating warehouse efficiency, as it reflects how many times inventory is renewed within a year and how effective stock management is. From the reviewed literature, the investigations in Ref [10] stands out by reporting an annual turnover of 9.2 cycles in a company within the technological sector which demonstrates a more agile and productive use of inventory. This result suggests that reaching or approximating this level constitutes a solid benchmark of efficiency in operations where demand tends to be dynamic and shifting.

### B. *Incorrect Inventory Recording Procedures*

Studies analyzing failures in inventory recording procedures consistently show that automatic identification technologies deliver significantly better performance than manual methods. Evidence demonstrates that RFID achieves the highest level of accuracy due to its ability to record information in real time with minimal human intervention. Among the cases evaluated, one stands out by achieving 90% accuracy in data capture and raising inventory accuracy to an ERI of 97%, the highest value found in this type of application [15]. Its effectiveness is further confirmed by results showing an increase in accuracy from 69% to 90% after RFID was incorporated into the system [18]. Additionally, research demonstrates that process standardization practices such as cycle counting significantly improve record quality, even without exclusively relying on advanced technological solutions [11]. Overall, these studies show that RFID provides the most consistent results, although it can be complemented with simpler operational methodologies to achieve additional improvements.

### C. *Inacurate Demand Forecasting*

Regarding studies addressing demand forecasting, the literature indicates that time series constitute an essential tool for analyzing the evolution of a variable over time and anticipating future behavior. As explained in the reviewed works, this type of analysis helps identify trends, cycles, and variations that are crucial for properly planning inventory needs [19]. Research also confirms that models such as ARIMA and LSTM significantly improve forecasting accuracy by capturing both linear structures and more complex dynamics, thereby reducing costs associated with excess inventory and stockout events [16].

### D. *High Picking Times*

Studies focusing on picking efficiency particularly related to time reduction show that process performance largely depends on adequate warehouse design and the use of advanced methodologies. The combination of SLP with approaches such as entropy-based optimization or Lean 4.0 makes it possible to reorganize space, reduce travel distances, and standardize activities, generating substantial improvements in order preparation times. Collectively, these findings show that solutions integrating layout redesign, waste elimination, and technological support offer the most consistent advances for optimizing operational performance in modern warehouses [21] , [22].

### E. *Low Turn-Over Products*

Among the studies reviewed, those incorporating multicriteria approaches into classification processes stand out, as they show the most robust results. One case applies the Neutrosophic Fuzzy EDAS method, which simultaneously evaluates factors such as demand, criticality, and cost, while another uses a Fuzzy AHP–TOPSIS model integrated with ABC, combining criterion prioritization with more precise product selection [13], [22]. In conclusion, these studies demonstrate that both approaches achieve more complete and reliable classifications, outperforming traditional techniques and offering better guidance for managing low-turnover inventory items.

## III. Contribution

Based on the findings in the literature, the following contribution is proposed as an improvement model for the company under study. This contribution is presented through a conceptual model that outlines the project's phases, components, and sequence of activities, as well as the relationships between each stage, providing a structured view of the methodology and guiding the development of the case (see Figure 1).

### *A. Foundations*

The proposal considers the use of advanced warehouse management tools, such as process standardization and the application of RFID within the Industry 4.0 framework, which help prevent incorrect inventory recording procedures and improve the accuracy of internal control. This is complemented using time series analysis, which enables more reliable demand forecasting and alignment of purchasing decisions with real needs. Additionally, an SLP will be developed to reorganize the internal warehouse layout and reduce product picking times, strengthening operational efficiency. Finally, an ABC classification integrated with a fuzzy logic model will be applied to optimize inventory categorization, assign low-turnover products more precisely, and improve decision-making regarding their management.

The combination of these tools enables a comprehensive warehouse management approach. They encompass all internal operations and strengthen visibility and control over product and information flows which start from reception to recording, placement, storage, and later dispatch. By organizing and making these stages more transparent, error detection is facilitated, unnecessary times are reduced, and inventory handling accuracy is improved. All of this is essential to achieving greater operational efficiency and a better capacity to adapt to the challenges faced by the supply chain in the telecommunications sector.

### *B. Proposed Model*

According to the analysis presented, the company faces a significant accumulation of inventory, evidenced by a low turnover rate. This scenario requires intervention, as it increases costs, immobilizes resources, and reduces the company's ability to react to market changes, preventing it from achieving the expected benefits. Based on this need, a solution is proposed that will generate operational improvements reflected in cost reduction and increased profitability. To do so, the root causes of the problem are examined, including incorrect inventory recording procedures, inaccurate demand forecasts, high average picking times, and the presence of low-turnover products. From this diagnosis, a model is proposed that addresses each of these causes and, through their integration, counteracts the problem, optimizes warehouse performance, and improves overall supply chain performance.

The model is developed based on the literature reviewed, where several approaches addressing similar issues were identified, offering tools that can be effectively applied in the company. In this model, the inputs correspond to the identified problem and its underlying causes, while the outputs represent the expected results once the project is implemented. Between these two ends, the phases of the project and the selected components are structured so that the model can effectively tackle the problem's root causes and enhance warehouse performance.

Regarding the tools, the authors in Ref [15] and Ref[23] indicate that the application of Industry 4.0 technologies such as RFID enables greater inventory visibility, reduces recording errors, and accelerates product identification, improving service levels and decreasing costs associated with losses and manual counting. Meanwhile, the studies in Ref [11] and Ref [24] emphasize that process standardization contributes to making operations more stable, repeatable, and controllable, achieving shorter lead times, lower variability, and the reduction of unnecessary activities.

Similarly, the studies in Ref [16] and Ref [19] argue that the application of time series models enhances demand forecast accuracy, enabling more effective planning of purchases and replenishments while reducing inventory accumulation.

Additionally, the investigations in Ref [20] and Ref [21] conclude that SLP improves the warehouse's physical layout, optimizes material flows, and reduces worker travel distances, resulting in operational savings and greater speed in daily activities. Finally, regarding the application of ABC classification with fuzzy logic, the authors in Ref [22] and Ref [23] state that it allows technological products to be classified more realistically by considering multiple criteria, enabling better prioritization of critical items and the definition of more efficient control policies. The conceptual design of the proposed model is illustrated below (see Figure 1).

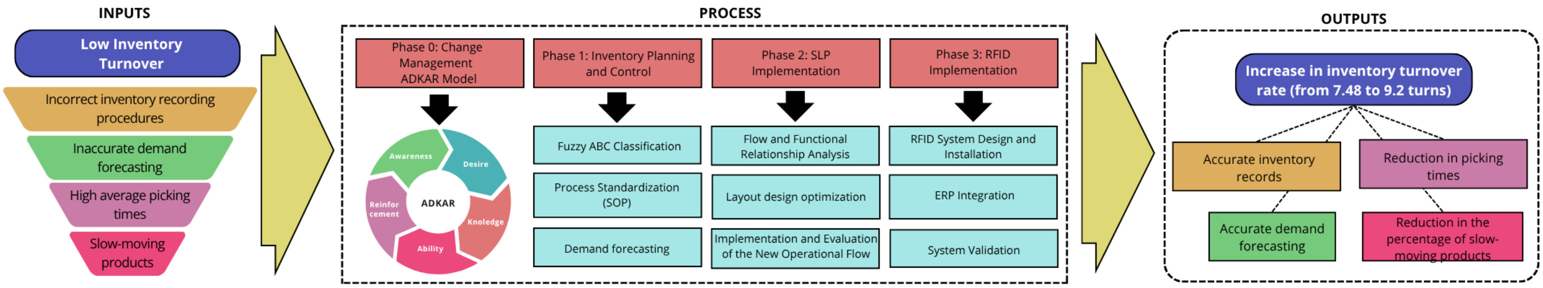


Fig 1. Conceptual Model

### C. *Initial Diagnosis*

The initial diagnosis of the problem is supported by indicators that evaluate warehouse performance across key areas. The main indicator will be inventory turnover, as it clearly reflects how quickly technological products move and reveals the level of stock accumulation. Supporting indicators are also included to provide a more detailed assessment of internal procedures. The first is inventory record accuracy (ERI), which measures the match between physical stock and system records. Next is the Mean Absolute Percentage Error (MAPE), which evaluates demand forecast accuracy and helps anticipate replenishment needs. The average picking time will also be assessed, as it shows the efficiency of order-preparation activities within the warehouse. Finally, the percentage of low-turnover products will be analyzed, revealing which items have minimal rotation and generate unnecessary accumulation. Together, these indicators will provide a clear picture of the current situation and serve to monitor the real impact of the proposed improvements. These indicators and their corresponding values are presented below (see Table 1).

TABLE I
INDICATOR AS IS

| INDICATOR | AS IS |
|---|---|
| Inventory Rotation (cycles/year) | 7.48 cycles |
| Slow moving Inventory (%) | 38.30% |
| Inventory accuracy (%) | 80.60% |
| MAPE (%) | 20.40% |
| Picking Time (min) | 17.8 min |

### D. *Development*

*The design and development of the solution are divided* into four phases aimed at addressing the four root causes of low inventory turnover. Work begins with Phase 0, which is supported by the implementation of change management using the ADKAR methodology [25].

In Phase 1, the ABC model with fuzzy logic will first be applied to classify the company's 130 products. The process includes defining evaluation criteria, constructing the decision matrix, normalizing quantitative criteria, and transforming qualitative criteria through fuzzy values. Then, weights are assigned and the Global Importance Index (IGI) is calculated, allowing the classification of products into A, B, and C categories to guide inventory prioritization. After the fuzzy ABC classification, process standardization will be implemented through the 5S methodology and cycle counting. The 5S methodology sort, set in order, shine, standardize, and sustain will organize the warehouse, reduce unnecessary times, and ensure more efficient working conditions. Subsequently, cycle counting will be performed according to the fuzzy ABC categorization, defining review periods based on the level of importance, enabling continuous and accurate inventory control.

Additionally, time series will be applied to forecast demand for the main products in each family. First, the ABC analysis will identify the relevant items; then, the series will be examined using plots, the autocorrelation function, and the partial autocorrelation function to determine trend and seasonality. From this, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model will be selected according to the Akaike Information Criterion. Finally, performance will be validated using residual analysis and the Mean Squared Error (MSE) and MAPE indicators, resulting in forecasts that support purchasing planning.

In Phase 3, RFID implementation will take place in three stages: system design and installation, ERP integration, and validation. The first stage includes designing the RFID system and installing the equipment in the warehouse, defining the work plan with the provider and establishing the necessary information exchange. The second stage integrates RFID with the ERP to ensure automatic inventory recording, as well as training staff on new policies and tools. Finally, the validation stage verifies system performance in real operations, monitoring reading accuracy and evaluating results through continuous follow-up and periodic meetings. A flowchart detailing the steps for implementing the proposed model is presented below (see Figure 2).

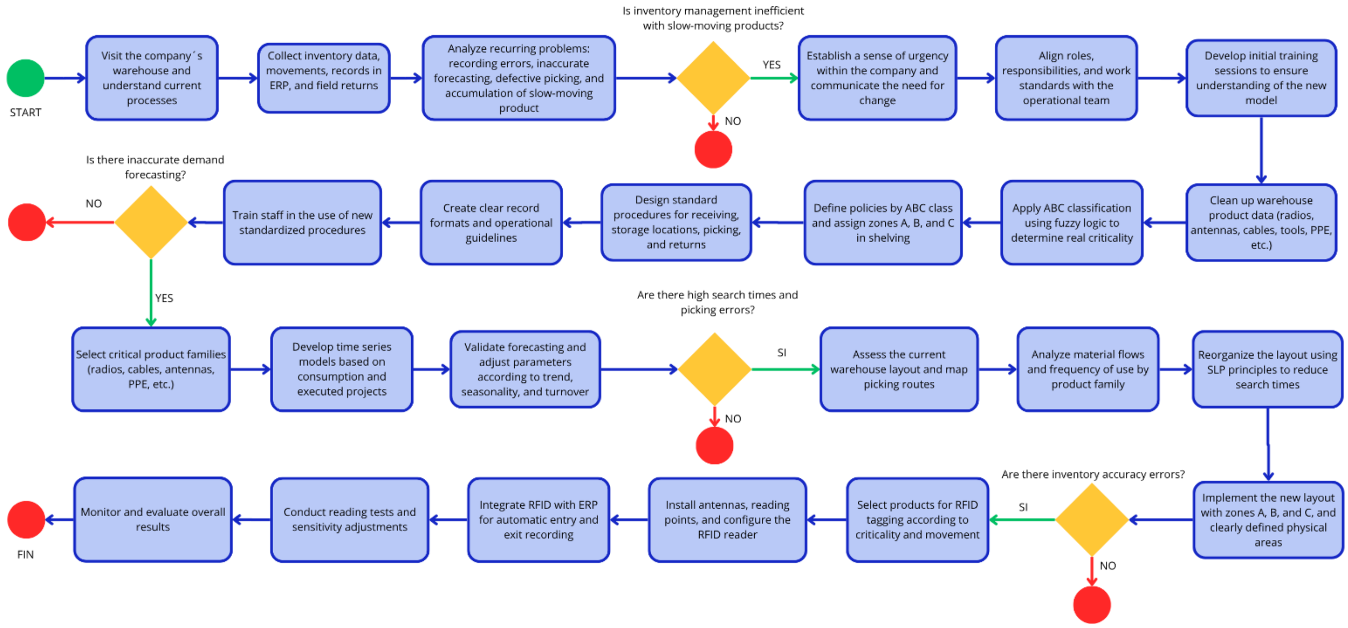


Fig 2. Implementation Flowchart

## *E. Final Diagnosis*

The main indicator, inventory turnover, is expected to reach 9.2 cycles per year, reflecting a significant improvement in product outflow speed. Additionally, the proportion of low-turnover products is expected to be reduced to 11%, minimizing the accumulation of low-movement items. For inventory record accuracy, the goal is to reach an ERI of 95%, strengthening stock control reliability. Regarding demand forecast precision, the target is a MAPE of 10%, ensuring more accurate projections for purchasing planning. Finally, in terms of operational efficiency, the average picking time is expected to be reduced to 12.15 minutes, optimizing internal flow and enabling faster product location within the warehouse. The expected indicator results for this project are summarized below (see Table 2).

TABLE II
EXPECTED INDICATOR RESULTS

| INDICATOR | AS IS | TO BE | VARIATION |
|---|---|---|---|
| Inventory Rotation (cycles/year) | 7.48 cycles | 9.2 cycles | 1.72 cycles |
| C Clasification Inventory (%) | 38.30% | 11% | 40% |
| Inventory accuracy (%) | 80.60% | 95% | 15% |
| MAPE (%) | 20.40% | 10% | 9.60% |
| Picking Time (min) | 17.8 min | 12.15 min | 5.3 min |

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