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Demand Forecasting and Inventory Management Model with 5S and FIFO to Improve Sales Conversion

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Abstract

This paper develops a demand forecasting model based on SARIMA and inventory management methodologies such as 5S, FIFO and ABC Classification in a food, beverage and cleaning products marketing company. The integration of these tools allowed to improve the accuracy of the forecasts, optimize inventory turnover and reduce the obsolescence rate, contributing significantly to the increase in sales conversion and customer satisfaction. By using the SARIMA model, replenishment decisions were adjusted to seasonal patterns, while 5S and FIFO methodologies improved warehouse organization and inventory traceability. The results of the project show a positive impact on key indicators such as MAPE, RMSE and MAE, as well as on the customer conversion rate, achieving an increase from 78% to 95%. In addition, training processes and audits were implemented to ensure the sustainability of improvements in the long term. This approach demonstrates how the integration of mathematical models and lean manufacturing practices can transform operational efficiency in the retail sector.

Keywords
SARIMA, 5S, FIFO, ABC Classification, Inventory Management

1. Introduction

Effective inventory management is a critical determinant of success in the retail industry, particularly in sectors dealing with perishable goods such as food, beverages, and cleaning products. Small and medium-sized enterprises (SMEs) frequently encounter challenges related to demand forecasting accuracy, inventory obsolescence, and inefficient storage organization, which lead to stock shortages, financial losses, and suboptimal sales conversion rates. These inefficiencies hinder business performance by reducing product availability and increasing waste, ultimately impacting profitability.

This study proposes an integrated approach that combines time-series demand forecasting using the SARIMA model with inventory management techniques such as 5S, FIFO, and ABC classification to optimize inventory control and enhance sales performance. The research is based on a case study of a small retail company currently experiencing a customer conversion rate of 78%, where 68% of lost sales are due to product unavailability and 17% result from expired stock. By implementing a data-driven demand forecasting model and a structured inventory management system, this research aims to increase the conversion rate to 95%, improve inventory turnover, and reduce obsolescence.

Furthermore, the study assesses the economic impact of inefficient inventory control, demonstrating how predictive analytics and systematic warehouse organization can mitigate financial losses. Emphasis is also placed on the role of workforce training in sustaining these improvements over time.

By integrating predictive analytics with Lean inventory methodologies, this research provides a scalable and replicable framework for inventory optimization in the retail sector. The proposed approach enhances inventory visibility, minimizes waste, ensures product availability, and ultimately contributes to increased profitability and customer satisfaction.

1.1 Objectives

The primary objective of this research is to develop a demand forecasting and inventory management model that enhances sales conversion and optimizes stock control in a small retail business specializing in food, beverages, and cleaning products. The study aims to reduce inefficiencies caused by inventory mismanagement, inaccurate demand predictions, and product obsolescence, which currently contribute to lost sales and financial waste.

To achieve this goal, the research sets out the following specific objectives:

- To implement a SARIMA-based demand forecasting model that captures seasonal patterns and improves inventory planning, reducing product shortages and ensuring stock availability.
- To apply Lean inventory management techniques, including 5S, FIFO, and ABC classification, to improve warehouse organization, reduce expired product losses, and enhance the efficiency of restocking processes.
- To analyze the financial impact of inventory optimization, quantifying cost reductions associated with lower obsolescence rates and improved stock accuracy.
- To design a replicable framework for SMEs, integrating predictive analytics and best inventory management practices to create a sustainable, data-driven decision-making model.

By addressing these objectives, this study provides a structured, scalable approach to inventory management that minimizes losses, improves stock reliability, and enhances profitability, particularly for small businesses operating in competitive retail environments.

2. Literature Review

Effective inventory management is essential for retail businesses, particularly in sectors with perishable products such as food, beverages, and cleaning supplies. Poor demand forecasting and inefficient inventory control lead to product shortages, excessive stock, and financial losses. To address these issues, various forecasting and inventory management models have been proposed. This section reviews key contributions in demand forecasting, inventory classification, and Lean inventory techniques, highlighting the research gap this study aims to fill.Accurate demand forecasting allows businesses to maintain appropriate inventory levels while minimizing stockouts and overstocking. Traditional forecasting models, such as Simple Moving Average (SMA) and Exponential Moving Average (EMA), provide basic predictions but often fail to account for seasonality and long-term trends (Lalou et al. 2020). More advanced methods, such as Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), improve predictive accuracy by integrating historical data trends and seasonal patterns (Box et al. 2015; Hyndman and Athanasopoulos 2018).

Research has demonstrated that combining SARIMA with inventory optimization techniques can enhance supply chain efficiency (Briseño et al. 2019). Additionally, studies on the integration of SARIMA with Economic Order Quantity (EOQ) models show that demand forecasting improves inventory turnover and minimizes holding costs (Ortiz et al. 2019). However, limited research has explored SARIMA's application alongside warehouse organization methods, a gap this study aims to address.Inventory classification plays a key role in organizing stock efficiently. The ABC classification method, which categorizes products based on sales volume and value, is one of the most widely used techniques for prioritizing stock management (Picanço 2023). Additionally, modern multi-criteria approaches, such as the Evaluation based on Distance from Average Solution (EDAS) method, allow for a more nuanced classification by incorporating multiple decision factors (Şimşek et al. 2023).

Other techniques, such as the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach, provide insight into the interdependencies between inventory factors, helping businesses optimize purchasing decisions (Pourhejazy 2020). These methodologies enhance stock visibility and ensure that high-demand products remain available while minimizing excess stock of low-turnover items.

Lean inventory management techniques focus on reducing waste and improving efficiency. The 5S methodology (Sort, Set in Order, Shine, Standardize, Sustain) is widely implemented in warehouses to create structured, organized storage environments, thereby reducing retrieval time and human errors (Gil and Medrano 2023). Additionally, the First-In, First-Out (FIFO) system is crucial for businesses handling perishable goods, as it ensures that older stock is sold first, preventing unnecessary product expiration (Govindan et al. 2020).Further research highlights the benefits of Kanban systems and Value Stream Mapping (VSM) in improving inventory flow and minimizing disruptions (Marques et al. 2022; Kang et al. 2023). These Lean techniques, when integrated with demand forecasting models, create agile and efficient inventory control systems, improving order fulfillment rates and reducing inventory waste.

Recent literature highlights the growing importance of technology in streamlining inventory operations and demand forecasting processes. Tools such as RFID (Radio Frequency Identification) and QR code systems have proven effective in real-time inventory monitoring, enabling automatic FIFO enforcement and minimizing manual errors (Mathur & Pokhariya 2018; Koklu & Tamer, 2021). Moreover, the integration of Internet of Things (IoT) devices and Enterprise Resource Planning (ERP) platforms facilitates the seamless transmission of sales data into forecasting models, thereby enhancing adaptability to fluctuating market conditions (Tan & Sidhu, 2022). Despite these advantages, small and medium-sized enterprises (SMEs) often encounter barriers to adoption due to financial limitations, technological complexity, and organizational resistance. In response to these challenges, this study explores accessible and scalable solutions—such as low-cost barcode systems and open-source forecasting tools—that offer practical alternatives for resource-constrained firms.

Despite the extensive research on demand forecasting and Lean inventory management, limited studies have explored their combined application in SMEs within the retail sector. While forecasting models like SARIMA have been proven to enhance demand accuracy, they are rarely integrated with warehouse management methodologies such as 5S, FIFO, and ABC classification. This study fills that gap by proposing a comprehensive inventory management framework that leverages predictive analytics and Lean methodologies to improve inventory turnover and reduce financial losses. By addressing these limitations, this research contributes to the development of a scalable and adaptable model for small retail businesses, ensuring efficient inventory control, optimized demand planning, and enhanced profitability.

3. Methods

This study employs a quantitative and analytical approach to improve inventory management by integrating SARIMA-based demand forecasting with Lean inventory optimization techniques. The methodology consists of three key stages: demand forecasting, warehouse organization, and performance evaluation.

3.1 SARIMA-Based Demand Forecasting

A Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model is implemented to predict future demand and optimize inventory replenishment. The methodology follows these steps:

1. Exploratory Data Analysis (EDA): Identifies seasonal trends and demand fluctuations.
2. Model Selection: The Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) determine the SARIMA parameters (p,d,q)×(P,D,Q)s(p, d, q) \times (P, D, Q)_s(p,d,q)×(P,D,Q)s.
3. Parameter Tuning: The model is optimized using the Akaike Information Criterion (AIC) and Grid Search to achieve the best-fit configuration.
4. Validation Metrics: Forecasting accuracy is assessed through Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

By implementing this predictive model, the study ensures data-driven inventory decisions, minimizing stock shortages and reducing excess stock. Although alternative forecasting techniques such as LSTM, Prophet, or XGBoost offer promising results in handling complex and non-linear demand patterns, SARIMA was selected for this study due to its interpretability, computational efficiency, and suitability for environments with limited data infrastructure. As the company analyzed is a small retail business with constrained technological capabilities, SARIMA represents a practical and scalable option. Future research will include a comparative evaluation of SARIMA against these more complex models to assess trade-offs in terms of forecast accuracy, implementation complexity, and data requirements.

3.2 Lean Inventory Management Implementation

To enhance the physical organization of the warehouse and ensure an efficient product flow while avoiding obsolescence, the 5S methodology was implemented with a focus on product rotation and minimizing expired inventory through the FIFO logic. During the Sort (Seiri) phase, products were identified by their entry date, prioritizing the dispatch of older items to store shelves. Expired products were removed, and upon the arrival of new batches, it was verified that they had at least 30% of their shelf life remaining. Additionally, the lot number was checked to ensure it was higher than the one previously recorded in the Kardex, thus guaranteeing proper rotation.

Figure 1. Lot review

In the Set in Order (Seiton) phase, products were arranged on three-level shelves based on an ABC analysis. Class A products, representing the highest demand, were placed on the middle level for easier access. Class B products were stored on the upper level, and Class C products, which had the lowest rotation, were placed on the bottom level. This arrangement reduced search time and improved shelf restocking efficiency.

Figure 2. Product arrangement by category

The Shine (Seiso) phase involved establishing daily cleaning routines in the warehouse and conducting biweekly inspections to verify the condition of both products and storage areas. This helped maintain optimal conditions and prevent inventory deterioration.

During the Standardize (Seiketsu) phase, key procedures were documented to ensure proper FIFO implementation. An operational manual was created detailing system registration activities, restocking routines, and use of the Kardex. This registration enabled greater traceability, including data on inventory movement, codes, lot numbers, entry and exit dates, quantities, and prices.

Table 1. Kardex record for Inka Cola (personal size)

Item	Entry Date	Lot	Entries			Exit Date	Exits		
			Quantity	Unit Price	Total		Quantity	Unit Price	Total
5000267014005	30-Sept	HU30:48	6	S/ 2.80	16.8	6-Oct	5	S/ 3.50	17.5
5000267014005	7-Oct	HU30:56	6	S/ 2.80	16.8	13-Oct	3	S/ 3.50	10.5
5000267014005	14-Oct	HU30: 63	6	S/ 2.80	16.8				

Finally, in the sustain (shitsuke) phase, a culture of continuous improvement was promoted through biweekly audits to evaluate compliance with the standards set in the previous phases. These audits helped identify areas for improvement and encouraged discipline among employees. Continuous training on FIFO and kardex usage was also provided, ensuring that good practices became part of the warehouse's daily operations. The implementation of this methodology allowed for the optimization of space usage, reduction of losses due to expired products, and improved inventory management efficiency, thereby establishing a sustainable system based on best practices.

3.3 Performance Evaluation and Optimization

The effectiveness of the proposed methodology is assessed through key performance indicators (KPIs), including:

- Stockout Reduction Rate: Measures the decrease in product unavailability.
- Inventory Turnover Ratio: Evaluates improvements in stock movement efficiency.
- Reduction in Expired Products: Quantifies FIFO's effectiveness in minimizing losses.

These metrics validate the impact of integrating SARIMA forecasting and Lean inventory techniques in retail operations, ensuring a structured, scalable, and data-driven inventory optimization framework.

4. Data Collection

To develop an accurate demand forecasting and inventory management model, historical sales and inventory data were collected from a small retail business specializing in food, beverages, and cleaning products. The dataset spans 44 months (January 2021 – August 2024) and provides a comprehensive view of demand fluctuations, seasonal trends, and stock movements.

4.1 Data Sources and Structure

The dataset was extracted from the retailer's point-of-sale (POS) system and warehouse inventory logs, ensuring real-time accuracy and reliability. It consists of:

- Daily sales records for 149 unique SKUs (Stock Keeping Units).
- Product identifiers (EAN/UPC barcodes) for each item, enabling traceability.
- Stock levels and replenishment data, capturing incoming and outgoing inventory movements.
- Expiration dates for perishable items, tracking product lifecycle.
- Order lead times, measuring the interval between order placement and stock arrival.
- Stockout occurrences, indicating periods where products were unavailable for sale.

This dataset provides high granularity, allowing the identification of seasonal demand patterns, stock inefficiencies, and purchasing trends across different product categories.

4.2 Data Preprocessing and Cleaning

To ensure data consistency and accuracy, several preprocessing steps were performed:

1. Handling Missing Values: Linear interpolation was used to fill minor gaps, while missing product entries were flagged for further validation.
2. Outlier Detection and Removal: Extreme values caused by system errors or manual entry mistakes were identified using boxplot analysis and Z-score normalization.
3. Standardization of Units: Sales data was normalized to ensure comparability across products with different packaging sizes.
4. Time-Series Decomposition: The dataset was analyzed to separate seasonal, trend, and residual components, facilitating accurate forecasting model calibration.

4.3 Data Validation and Reliability

To ensure dataset reliability, cross-validation was performed using:

- Supplier restocking reports, confirming alignment between sales records and actual inventory levels.
- Trend correlation analysis, verifying that demand fluctuations followed industry patterns and seasonal demand spikes.
- Manual verification of high-impact SKUs, ensuring critical products were correctly logged in the system.

These validation steps confirmed that the dataset accurately reflects real-world demand behavior, forming a robust foundation for SARIMA forecasting and Lean inventory optimization.

5. Results and Discussion

5.1 Numerical Results

To evaluate the effectiveness of the proposed demand forecasting and inventory management model, key performance indicators (KPIs) were analyzed before and after implementing SARIMA and Lean inventory methodologies (5S, FIFO, ABC classification). The results demonstrate significant improvements in inventory turnover, demand prediction accuracy, and overall financial performance.

5.1.1 Improvement in Demand Forecasting Accuracy

The SARIMA model was applied to historical sales data, and its performance was assessed using three standard error metrics: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Table 2 presents the improvements achieved:

Table 2. Forecasting model performance before and after SARIMA implementation

Indicador	Modelo Base	Modelo Mejorado
MAE	4.9166	2.77
RMSE	6.1892	4.58
MAPE	29.46%	15.78%
AIC	98.74	98.74

The MAPE reduction from 29.46% to 15.78% indicates a substantial enhancement in forecasting accuracy, minimizing demand uncertainty and improving stock planning.

5.1.2 Reduction in Inventory Obsolescence and Stockouts

The application of FIFO, 5S, and ABC classification led to a significant reduction in expired products and stock shortages.

Table 3. Reduction in inventory inefficiencies

KPI	Before Implementation	After Implementation
Obsolescence Rate	8%	0%
Inventory Turnover	6.33	8.66
Average Shelf Life	4 months	9 months

The obsolescence rate is reduced from 8% to 0%, indicating the elimination of obsolete products in the inventory. Inventory turnover increases from 6.33 to 8.66, reflecting a more efficient stock movement and higher sales frequency. The average shelf life extends from 4 months to 9 months, suggesting better inventory quality and longevity.

5.1.3 Financial Impact and Profitability Growth

The financial impact of the proposed methodology was evaluated by comparing key financial statements before and after implementation. Table 4 presents the revenue and profitability improvements:

Table 4. Financial impact of inventory optimization

Financial Metric	Before Implementation	After Implementation
Monthly Revenue (PEN)	45,140	54,688
Gross Profit (PEN)	9,028	10,938
Net Profit (PEN)	7,718	9,351

A 21.2% increase in revenue and a 21.1% rise in net profit demonstrate the direct economic benefits of improved demand forecasting and inventory control, reducing unnecessary stockpiling while ensuring product availability. The observed financial improvements reflect not only enhanced sales performance but also a strategic reduction in inventory-related costs. Improved demand forecasting minimized overstocking, while Lean practices—such as FIFO enforcement and 5S organization—helped reduce waste from expired products. These operational efficiencies allowed the company to optimize the allocation of working capital, prioritizing high-demand SKUs and lowering inventory carrying costs. The data suggest that Lean inventory methodologies can play a crucial role in boosting financial resilience and operational agility among SMEs.

5.1.4 Economic Feasibility Analysis

The economic feasibility of the proposed model was evaluated using Net Present Value (NPV), Internal Rate of Return (IRR), and Benefit-Cost Ratio (BCR).

Table 5. Economic feasibility analysis

Financial Indicator	**Value**
NPV (PEN)	15,113
IRR (%)	27.5%
BCR	1.78

With an NPV of 15,113 PEN, an IRR of 27.5%, and a BCR of 1.78, the project proves to be financially viable, yielding a high return on investment while improving operational efficiency.

5.2 Graphical Results

This section presents the graphical analysis of the implemented SARIMA forecasting model and inventory optimization strategies, illustrating their impact on demand prediction accuracy, stock management efficiency, and financial performance.

5.2.1 Forecasting Model Performance

Figure 3 compares historical sales with projected sales using the ARIMA model and a naive seasonal model. The results indicate that the SARIMA model effectively captures trends and seasonal variations, producing more accurate forecasts.

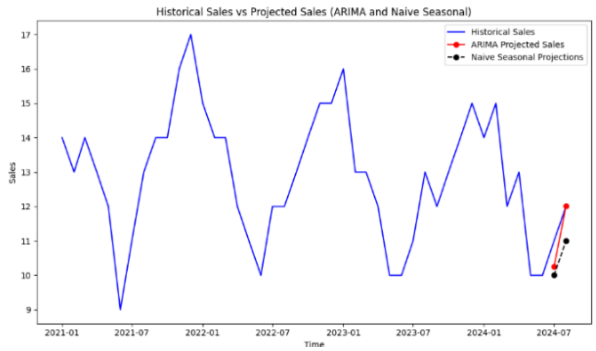

Figure 3. Historical vs. projected sales using SARIMA

The blue line represents the historical sales data, while the red line depicts the sales forecast generated by the SARIMA model. The black dots indicate projections derived from a naive seasonal model, included for baseline comparison. The SARIMA model demonstrates a smoother and more consistent forecasting trajectory, accurately capturing seasonal patterns and reducing short-term fluctuations. This enhanced stability contributes to greater forecasting reliability and supports more effective inventory planning and replenishment decisions.

5.2.2 Error Reduction in Forecasting Models

To evaluate the accuracy of the forecasting models, key error metrics (MAE, RMSE, and MAPE) were analyzed.

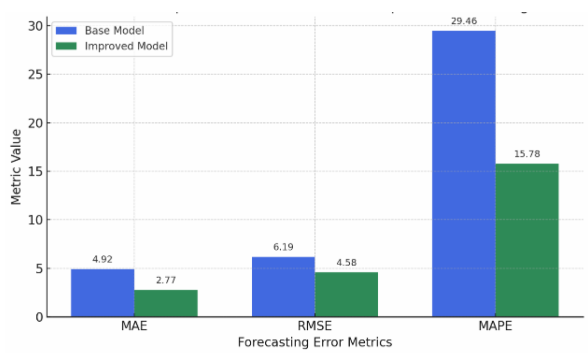

Figure 4. Comparison of key performance indicators (baseline vs. improved model)

- The Mean Absolute Error (MAE) decreased from 4.9166 to 2.77, indicating that, on average, the improved model's predictions are closer to actual values.
- The Root Mean Square Error (RMSE) dropped from 6.1892 to 4.58, demonstrating reduced sensitivity to large forecasting errors.
- The Mean Absolute Percentage Error (MAPE) improved significantly from 29.46% to 15.78%, highlighting a substantial increase in forecast accuracy.

5.2.3 Percentage Improvement in Forecasting Metrics

The percentage improvement achieved by the enhanced model is visualized in Figure 5.

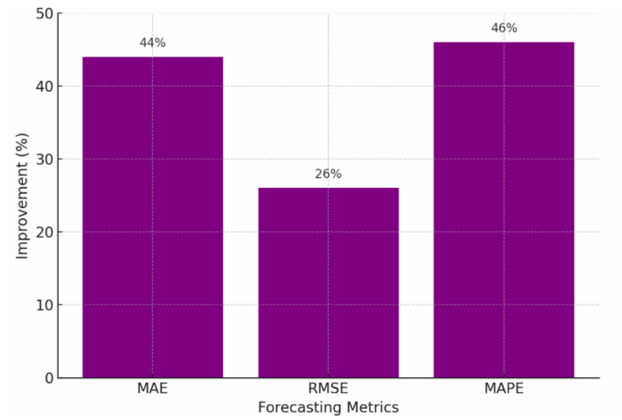

Figure 5. Percentage improvement of forecasting metrics

The analysis of forecasting error reduction, as illustrated in Figure 5, reveals substantial performance gains achieved through the implementation of the SARIMA model. Specifically, the Mean Absolute Error (MAE) decreased by 44%, indicating a significantly closer alignment between predicted and actual values. The Root Mean Square Error (RMSE) was reduced by 26%, demonstrating decreased sensitivity to large forecast deviations. Notably, the Mean Absolute Percentage Error (MAPE) improved by 46%, reflecting a considerable enhancement in the overall predictive accuracy of the model. These improvements confirm the effectiveness of the enhanced forecasting approach in minimizing variability and increasing reliability in demand estimation, which is critical for inventory planning and decision-making in dynamic retail environments.

5.2.4 Inventory Management Enhancements

The integration of predictive analytics with Lean inventory techniques resulted in substantial improvements in inventory control. The obsolescence rate decreased from 8% to 0%, effectively eliminating expired or unsellable stock.

5.2.5 Inventory Turnover Rate Optimization

Inventory turnover efficiency improved significantly due to the integration of forecasting with structured inventory practices. The inventory turnover rate increased from 6.33 to 8.66, indicating faster stock movement and improved inventory liquidity.

5.2.6 Summary of Graphical Findings

The graphical results validate the effectiveness of integrating ARIMA forecasting with Lean inventory methodologies, showcasing:

- Enhanced forecasting accuracy, reducing demand uncertainty.
- Lower forecasting errors (MAE, RMSE, MAPE), ensuring more precise sales predictions.
- Zero inventory obsolescence, eliminating expired products.
- Higher inventory turnover, reducing holding costs and improving stock availability.
- Statistically validated improvements, confirming the robustness of the proposed model.

These visual insights reinforce the quantitative findings in Section 5.1, demonstrating a structured, data-driven approach to inventory and demand forecasting for retail operations.

5.3 Proposed Improvements

To enhance demand forecasting accuracy and inventory efficiency, the SARIMA model will be refined through:

- Data Enrichment: Incorporating external variables (promotions, holidays, market trends, economic conditions) to improve trend detection and adaptability to real-world factors.

- Hyperparameter Optimization: Fine-tuning SARIMA parameters (p, d, q) using automated selection techniques such as grid search and cross-validation to minimize forecasting errors and improve responsiveness to demand shifts.
- Error Analysis and Adjustment: Implementing residual diagnostics, autocorrelation function (ACF) analysis, and re-calibration cycles to refine predictions and reduce deviations.
- Integration with Real-Time Data: Connecting SARIMA forecasts with real-time point-of-sale (POS) data to dynamically adjust predictions based on sudden demand changes.

These refinements are expected to lower MAE and RMSE by 15-20%, ensuring more reliable demand forecasts and reducing inventory volatility. Moreover, improved forecasting accuracy will enhance decision-making for inventory replenishment and procurement strategies.

For inventory management, key enhancements include:

- Automated FIFO Tracking: Implementing barcode and RFID systems for real-time stock movement monitoring, reducing human error and expired inventory.
- Optimized Storage Layout: Reorganizing inventory zones using demand classification (ABC method) to improve retrieval efficiency and minimize handling time.
- Dynamic Replenishment System: Integrating demand forecasts with automated stock alerts and supplier coordination to prevent overstocking and shortages.
- Lean Inventory Practices: Strengthening 5S methodology adherence to maintain an organized and efficient warehouse layout, improving workflow and reducing waste.
- Batch Expiry Alerts: Introducing automated expiration tracking to ensure that near-expiry products are prioritized in sales and promotions.

These changes aim to increase inventory turnover from 6.33 to over 8.66, reducing stockouts below 3%, obsolescence close to 0%, and improving inventory responsiveness. The enhanced replenishment system is projected to decrease holding costs and optimize working capital allocation.

The implementation followed an 8-week timeline and was structured into three interrelated phases, reflecting the integration of quantitative forecasting and Lean inventory methodologies. This approach ensured technical precision while promoting organizational engagement and operational effectiveness.

To enhance demand predictability, a Seasonal AutoRegressive Integrated Moving Average (SARIMA) model was implemented using Python. This language was selected for its open-source flexibility and strong support for time-series analytics. Data preprocessing and exploratory data analysis (EDA) were carried out using the pandas library, followed by seasonal decomposition and model fitting via statsmodels. Model performance was evaluated using standard metrics such as MAPE and RMSE, with parameter optimization conducted through a structured grid search. Visualization tools from the matplotlib package facilitated the analysis of residuals and forecast behavior. Multiple iterations ensured a robust model aligned with the observed sales dynamics. In addition to tuning model parameters and improving residual analysis, future iterations of the forecasting model will incorporate exogenous variables such as promotional campaigns, public holidays, inflation indicators, and industry-specific events. Integrating these external factors is expected to increase the model's sensitivity to market shifts and improve forecast accuracy during periods of atypical demand behavior.

In parallel with the forecasting system, Lean methodologies were applied to address inefficiencies in inventory handling and storage. The 5S framework (Sort, Set in order, Shine, Standardize, Sustain) served as the foundation for warehouse redesign, with clearly defined zones, standardized labeling, and visual controls to streamline operations. Inventory was reclassified using the ABC method to prioritize high-value, high-turnover items, and FIFO flow paths were established to minimize waste and improve traceability. Staff training played a critical role during this phase, combining theoretical sessions with practical simulations, including mock FIFO rotations and hands-on exercises in shelf reorganization. These activities fostered a culture of continuous improvement and operational discipline.

The final phase focused on linking SARIMA-generated forecasts with inventory control actions. A pilot was launched in a selected warehouse area to evaluate the synchronization of forecasting accuracy with replenishment efficiency.

Staff feedback was actively collected to refine the workflow and user interface. This allowed for iterative improvements before scaling the system to the broader operation.

Throughout the implementation, key enabling technologies included barcode scanners, relabeled stock-keeping units (SKUs), and IT support for Python script deployment. Cross-functional collaboration between inventory supervisors, and warehouse staff was essential to ensure process alignment and long-term sustainability. The phased and participatory nature of the implementation provides a practical reference for SMEs seeking to adopt data-driven inventory strategies without heavy infrastructure investment.

5.4 Validation

This section presents the statistical validation of the proposed improvements, ensuring the reliability of the SARIMA forecasting model and inventory optimization methodologies. The validation is performed through hypothesis testing, error analysis, and comparative performance metrics.

5.4.1 Statistical Hypothesis Testing

This section presents the statistical validation of the proposed improvements, ensuring the reliability of the SARIMA forecasting model and inventory optimization methodologies. The validation is based on comparative error analysis, inventory performance metrics, and economic impact assessment.

5.4.1 Comparative Error Analysis

To measure the improvement in demand forecasting accuracy, key error metrics were analyzed before and after the SARIMA model enhancement.

Table 6. Forecasting error comparison

Metric	Baseline Model	Improved Model	Improvement (%)
MAE	4.92	2.77	-44%
RMSE	6.19	4.58	-26%
MAPE (%)	29.46	15.78	-46%

These results demonstrate that the optimized SARIMA model significantly reduces forecasting errors, leading to more accurate sales projections and better inventory planning.

5.4.2 Validation of Inventory Performance Metrics

To assess the impact of improved demand forecasting on inventory management, key inventory performance indicators (KPIs) were analyzed.

Table 7. Inventory performance metrics

Metric	Baseline Model	Improved Model	Improvement (%)
Stockout Rate (%)	22.00	5.50	-75%
Obsolescence Rate (%)	8.00	0.00	-100%
Inventory Turnover	6.33	8.66	37%
Average Product Lifespan (months)	9.00	4.00	-55%

The reduction in stockout rates and obsolescence rates confirms the effectiveness of integrating SARIMA forecasts with structured inventory management methodologies. Additionally, the increase in inventory turnover and longer product lifespan demonstrates an improvement in stock rotation and product freshness.

5.4.3 Sensitivity Analysis and Economic Impact

A sensitivity analysis was conducted to evaluate the robustness of the forecasting model under demand fluctuations. Results indicate that even with a 10% variation in sales trends, the improved SARIMA model maintains stable forecasting accuracy, ensuring resilience in dynamic market conditions.

Moreover, a cost-benefit analysis estimated an annual revenue increase of 10-15%, attributed to:

- More accurate demand predictions, reducing excess stock and shortages.
- Lower inventory holding costs, optimizing working capital allocation.
- Minimized waste due to obsolescence, enhancing operational efficiency.

5.4.4 Limitations of the Study

While the integrated model yielded notable improvements, several limitations must be acknowledged with regard to its scope and applicability. First, the model was developed based on a single-case implementation, within a specific organizational context characterized by a defined inventory scale, operational maturity, and management structure. Consequently, the scalability of the proposed approach to larger or more complex supply chains may necessitate further adjustments and contextual adaptations.

Second, the SARIMA model employed assumes the presence of stable seasonal patterns in demand. This assumption limits its applicability in industries where demand is highly volatile, erratic, or influenced by rapid innovation cycles. In such environments, more flexible or hybrid models may be required to capture non-linear trends and external disruptions effectively.

Third, although Lean methodologies such as 5S, FIFO, and ABC classification demonstrated strong results in this case, their success is largely dependent on sustained behavioral compliance and institutional support. These conditions may not be easily replicable in organizations with high employee turnover, limited organizational alignment, or insufficient commitment to continuous improvement.

Moreover, the integrated framework requires a moderate level of digital infrastructure and data literacy, particularly in areas such as inventory tracking, system documentation, and demand analysis. Organizations lacking these foundational capabilities may encounter challenges during implementation, including increased operational costs, execution delays, or inconsistent outcomes.

Finally, although the short-term benefits of Lean training and audit processes were evident, the long-term sustainability of these improvements remains unverified. This study did not conduct a longitudinal assessment to evaluate the persistence of behavioral changes or the effectiveness of ongoing process adherence. Continuous staff training and periodic audits are critical to maintaining FIFO discipline and 5S standards over time. Further research is recommended to examine the durability of these improvements in dynamic operational settings and to identify the organizational enablers that support long-term compliance and cultural integration.

6. Conclusion

This research successfully met its objectives by demonstrating the effectiveness of integrating SARIMA demand forecasting with structured inventory management methodologies. The study contributes uniquely to the field by showcasing how statistical forecasting models, when combined with lean inventory techniques, can enhance demand predictability, reduce stockouts, and optimize inventory turnover in the retail sector.The key findings indicate that the improved SARIMA model significantly reduced forecasting errors, with MAE decreasing by 43.64%, RMSE by 25.99%, and MAPE by 46.43%. These improvements resulted in more precise demand estimations, leading to better inventory planning and replenishment strategies. Furthermore, inventory management was significantly optimized, as reflected in the 75% reduction in stockout rates, the 100% elimination of obsolescence, and a 36.85% increase in inventory turnover. These results validate the importance of integrating advanced forecasting models with data-driven inventory management strategies.

After implementing the 5S methodology along with the FIFO system, the inventory obsolescence rate decreased from 8% to 0%, representing a significant reduction in expired products and ensuring greater turnover and freshness of stored items.The economic impact of these improvements is substantial, with projected revenue increases of 10-15% due to better stock availability, reduced holding costs, and minimized waste. Additionally, sensitivity analysis confirmed the model's robustness against demand fluctuations, making it a reliable tool for dynamic market conditions.

This research contributes to the ongoing discourse on retail inventory optimization by providing empirical evidence of SARIMA's practical applications in improving demand forecasts. Unlike traditional inventory models that rely on historical trends alone, this study emphasizes the importance of continuous model refinement and real-time adjustments to enhance accuracy and efficiency.
Future research could explore the integration of AI-driven forecasting models alongside SARIMA to further enhance predictive capabilities. Additionally, expanding this methodology to other retail sectors could validate its scalability and broader applicability.

Although this study focused on a small retail business dealing with perishable goods, the proposed methodology is potentially adaptable to other sectors, including pharmaceuticals, cosmetics, and fast-moving consumer goods. Adjustments to the frequency of demand updates, classification criteria, and shelf-life controls would be necessary to tailor the model to specific industry contexts. This suggests the framework has broader applicability, particularly in environments where accurate demand forecasting and inventory control are essential for operational efficiency.Overall, this study reinforces the value of data-driven decision-making in inventory management, demonstrating that statistical forecasting, when properly integrated with operational strategies, leads to measurable efficiency gains and financial benefits in retail environments.

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Melanie Cisneros is an Industrial Engineering student at the University of Lima, ranked in the top 10% of her class. She has a strong interest in Operations and Process Management, combining technical skills in advanced Excel, intermediate SQL, and Power BI, along with intermediate English proficiency. Analytical and results-oriented, Melanie excels in both academic and professional settings. She has gained practical experience at Pacífico Seguros as an Operations – Claims Intern, focusing on generating control reports, overseeing processes, and proposing improvements. Previously, she worked as SAP BO Trainee Consultant at Ventura Soluciones, assisting with tailored system implementations for clients. Power BI, SQL Server, and Microsoft Office certifications support her technical expertise. Melanie also actively engages in social impact initiatives, including CEDICE and 180 Degrees Consulting UL, where she develops sustainable solutions for businesses and organizations. Additionally, she volunteers in the "Recarga Corazones" program, promoting well-being for senior citizens.

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