

Improvement Process to Increase Inventory Turnover through Random Forest and Slotting in a Solar Water Heater Trading Company

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Abstract

Low inventory turnover represents a recurring problem in trading companies, as it leads to high holding costs, capital immobilization, and deficiencies in service levels. This study proposes an improvement process aimed at increasing inventory turnover through the integration of a Random Forest-based demand forecasting model and a slotting strategy applied to the warehouse. The study is conducted in a Peruvian company engaged in the commercialization of solar water heaters, whose products exhibit seasonal demand variability. The methodology includes an analysis of the current situation, the development of a demand forecasting model, the reorganization of the warehouse based on product turnover, and the validation of the proposed solution through discrete-event simulation using Arena software. The results show an improvement in forecasting accuracy, a reduction in days of inventory coverage, and an increase in inventory turnover for critical products. Furthermore, the simulation demonstrates enhanced operational efficiency under the proposed scenario. The developed approach proves to be applicable to trading companies facing inventory management challenges and logistical decision-making constraints.

Keywords

Inventory turnover, Demand forecasting, Random Forest, Slotting, Discrete-event simulation

1. Introduction

Inefficient inventory management represents one of the primary challenges in trading companies due to its direct impact on operating costs, working capital, and customer service levels. Several studies indicate that low inventory turnover is often associated with deficiencies in demand planning and inadequate allocation of logistics resources, particularly in contexts where demand exhibits high variability or seasonality (Chopra and Meindl, 2023; Mardiah et al., 2021). In sectors related to energy products, such as solar thermal systems, these deficiencies are exacerbated by external factors such as weather conditions and promotional campaigns, increasing the risk of overstocking or stockouts.

In this context, recent literature highlights the use of machine learning techniques as an effective alternative to improve demand forecasting accuracy compared to traditional statistical models. Previous research demonstrates that algorithms such as Random Forest can capture non-linear relationships and handle intermittent demand patterns more accurately, thereby contributing to improved decision-making in inventory management (Güven et al., 2021; Xiong et al., 2024; Lin et al., 2025). However, several authors agree that improvements in forecasting accuracy alone do not guarantee enhanced operational performance unless they are complemented by appropriate physical warehouse organization and efficient material flow management.

Furthermore, studies on warehouse optimization indicate that the implementation of slotting strategies based on product turnover and access frequency reduces picking times and improves operational efficiency (Duque-Jaramillo et al., 2024). Nevertheless, a gap remains in the literature regarding the practical integration of machine learning-based forecasting models with slotting strategies and their validation through simulation. In response to this gap, the present study proposes an improvement process aimed at increasing inventory turnover through the integration of a Random Forest-based demand forecasting model and a slotting strategy, applied to a solar water heater trading company and validated through discrete-event simulation.

1.1 Objectives

To increase inventory turnover in a solar water heater trading company through the implementation of an improvement process that integrates Random Forest-based demand forecasting and warehouse reorganization through slotting.

Specific objectives:

- To develop a Random Forest-based demand forecasting model to improve demand estimation for critical SKUs.
- To design and implement a slotting strategy based on product turnover in order to optimize warehouse management.
- To validate the proposed improvement process by comparing the AS-IS and TO-BE scenarios using discrete-event simulation through the integration of Random Forest algorithms and slotting techniques.

2. Literature Review

Inventory turnover is a critical indicator in operations management due to its direct impact on logistics costs, service levels, and financial performance. The literature consistently indicates that low inventory turnover is commonly associated with deficiencies in demand planning and inefficient warehouse organization, particularly in trading companies with high product variety and variable demand (Chopra and Meindl, 2023; Mardiah et al., 2021).

In this context, recent studies emphasize the need to integrate advanced analytical tools with operational decisions in order to achieve sustainable improvements in inventory management. However, although prior research has independently addressed demand forecasting through predictive models and warehouse reorganization strategies, empirical evidence regarding their joint application and validation in real commercial environments remains limited. In response to this gap, the present study is grounded in the following literature-supported approaches:

A. Demand Forecasting Using Random Forest

Machine learning algorithms have demonstrated superior performance compared to traditional methods in scenarios characterized by high variability and non-linear relationships. In particular, the Random Forest algorithm enables the capture of complex interactions among multiple predictor variables, significantly improving demand forecasting accuracy and reducing the error associated with inventory planning (Güven et al., 2021; Xiong et al., 2024; Lin et al., 2025).

B. Warehouse Reorganization through Slotting

Slotting strategies based on product turnover and access frequency are widely documented as effective approaches to improving warehouse operational efficiency. Numerous studies show that their implementation reduces travel time and optimizes picking processes, thereby indirectly contributing to increased inventory turnover. In this regard, slotting is established as a key complement to demand forecasting in achieving comprehensive improvements in inventory management (Duque-Jaramillo et al., 2024).

3. Methods

The research is conducted using an applied and quantitative approach, structured into phases that enable the analysis of the low inventory turnover problem and the evaluation of an improvement proposal based on demand forecasting and warehouse reorganization. The methodology is summarized in the following phases:

- Phase 1: Diagnosis of the current situation.
The performance of the inventory system and warehouse organization was analyzed to identify the main causes of low turnover, considering operational indicators and product distribution.

- Phase 2: Data collection and preparation.
Historical sales and inventory data were collected for demand analysis and product classification..
- Phase 3: Forecasting model development.
A demand forecasting model was developed using the Random Forest algorithm, aimed at estimating demand for critical products.
- Phase 4: Improvement proposal design.
A warehouse reorganization proposal was designed through a slotting strategy based on product turnover.
- Phase 5: Analysis and validation.
The impact of the proposal was evaluated through discrete-event simulation by comparing the AS-IS and TO-BE scenarios.

4. Data Collection

4.1 Diagnosis of the Current Situation

The current situation of the solar water heater trading company reveals a reactive inventory management approach, primarily based on staff experience rather than analytical tools. To quantify operational efficiency, the Inventory Turnover Ratio (ITR) and Days of Coverage indicators were used, calculated using the following expressions (Figure 1):

$$\text{Inventory Turnover} = \frac{\text{Annual Cost of Sales}}{\text{Average Annual Inventory}}$$

$$\text{Days of Coverage} = \frac{365}{\text{Inventory Turnover}}$$

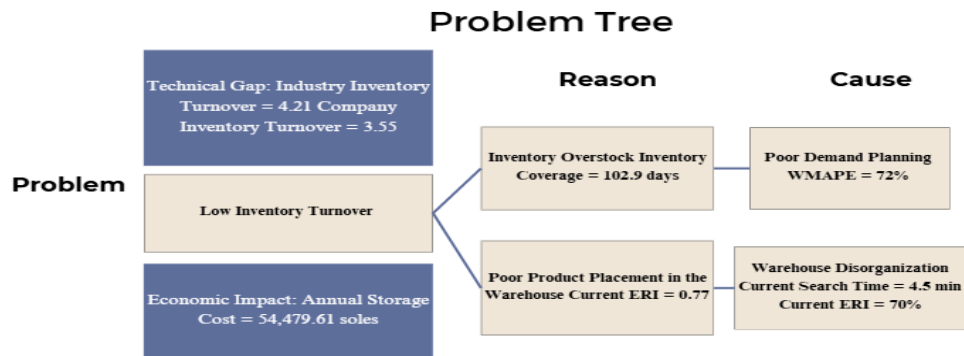


Figure 1. Inventory Turnover Diagnosis Tree

4.2 Data Collection and Preparation

Historical sales, inventory, and warehouse movement data were collected with weekly aggregation. Products were classified into critical and non-critical SKUs based on their turnover level and sales contribution. The inventory turnover indicator used as a reference was calculated as the average of the critical SKUs, as it more accurately represents the performance of the system under analysis (Table 1).

Table 1. Inventory Turnover in 2024 by SKU

SKU	2024 Inventory Turnover (turns/year)	Classification
100 L	7.8	Non-critical
150 L	7.2	Non-critical
200 L	3.7	Critical
300 L	6.5	Non-critical
500 L	3.4	Critical
Average of Critical SKUs	3.55	Internal baseline

The diagnosis revealed that the 200L and 500L SKUs exhibit an average turnover of 3.55 cycles per year, equivalent to coverage exceeding 100 days, resulting in significant capital immobilization. This situation is associated with a high forecasting error, measured using WMAPE, defined as:

$$WMAPE = \frac{\sum |Actual - Forecast|}{\sum Actual}$$

The literature indicates that advanced algorithms such as Random Forest can reduce forecasting error by 15% to 20%, while the implementation of slotting contributes to reducing warehouse operational times. In this context, the identified technical gap lies in the disconnection between demand prediction and the physical organization of inventory, positioning the company below the sector benchmark of 4.21 annual inventory turns.

4.3 Development of the Demand Forecasting Model

For the development of the Random Forest model, input variables and the target variable were defined based on the available historical data. The input variables include sales information and other relevant factors, while the target variable corresponds to the future demand of critical SKUs. The data were structured according to their temporal sequence to ensure the consistency of the analysis (Figure 2).

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# Create DataFrame
df = pd.DataFrame({
    'Actual_Sales': sales,
    'Min_Temp': min_temp,
    'Seasonality': seasonality,
    'Commercial_Promotions': commercial_events
})

# Create Lag-1 Feature
df['Lag1_Sales'] = df['Actual_Sales'].shift(1).fillna(df['Actual_Sales'].mean())

# 2. DATA SPLIT (80% Train, 20% Test)
train_size = int(n_weeks * 0.8)
train, test = df.iloc[:train_size], df.iloc[train_size:]

features = ['Lag1_Sales', 'Min_Temp', 'Seasonality', 'Commercial_Promotions']
X_train, y_train = train[features], train['Actual_Sales']
X_test, y_test = test[features], test['Actual_Sales']

# 3. RANDOM FOREST MODEL (Optimized Hyperparameters)
rf_model = RandomForestRegressor(
    n_estimators=500,
    max_features='sqrt',
    min_samples_leaf=5,
    random_state=42
)
rf_model.fit(X_train, y_train)

# 4. PREDICTIONS AND METRICS
predictions = rf_model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, predictions))
mape = mean_absolute_percentage_error(y_test, predictions)
wmape = np.sum(np.abs(y_test - predictions)) / np.sum(y_test)

print(f"--- MODEL PERFORMANCE METRICS ---")
print(f"Features used: {features}")
print(f"RMSE: {rmse:.2f}")
print(f"MAPE: {mape*100:.2f}%")
print(f"WMAPE: {wmape*100:.2f}%")

# 5. VISUALIZATION (OUTPUT IN ENGLISH)
plt.style.use('seaborn-v0_8-whitegrid')
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))

```

Figure 2. Random Forest Model Structure and Evaluation Metrics

This supervised learning method was selected for its intrinsic ability to model non-linear relationships and its robustness in the presence of high data variability (Wiyanti et al., 2021). The model architecture was based on a historical dataset comprising 208 weeks, incorporating exogenous variables that enable the capture of causal effects beyond internal trends, as detailed in Table 2.

Table 2. Model Variables and Data Description (n = 208)

Category	Variable	Description	Range / Unit
Target Variable	Sales	Weekly	0–150 units
Climatic	Minimum Temperature	Average weekly minimum temperatures	8.5°C - 21.0°C
Temporal	Seasonality	Cyclical encoding (Months/Weeks)	1 - 12 / 1 - 52
Commercial	Discount	Percentage discount applied during the week	0% - 30%

4.4 Design of the Improvement Proposal

The proposed macro model is based on a bidirectional information flow between predictive analytics and physical optimization. The model architecture is divided into three main layers:

- **Data Input Layer:** Collection of historical sales data categorized through One-Hot Encoding (100L to 500L) and seasonality variables.
- **Processing Layer (Random Forest):** A machine learning engine composed of an ensemble of decision trees that processes the non-linearity of solar water heater demand to generate a robust forecast.
- **Output and Action Layer (Slotting):** The projected demand feeds a classification algorithm that determines the optimal placement of critical SKUs within the warehouse, prioritizing proximity to the dispatch area for models with higher predicted turnover (Figure 3).

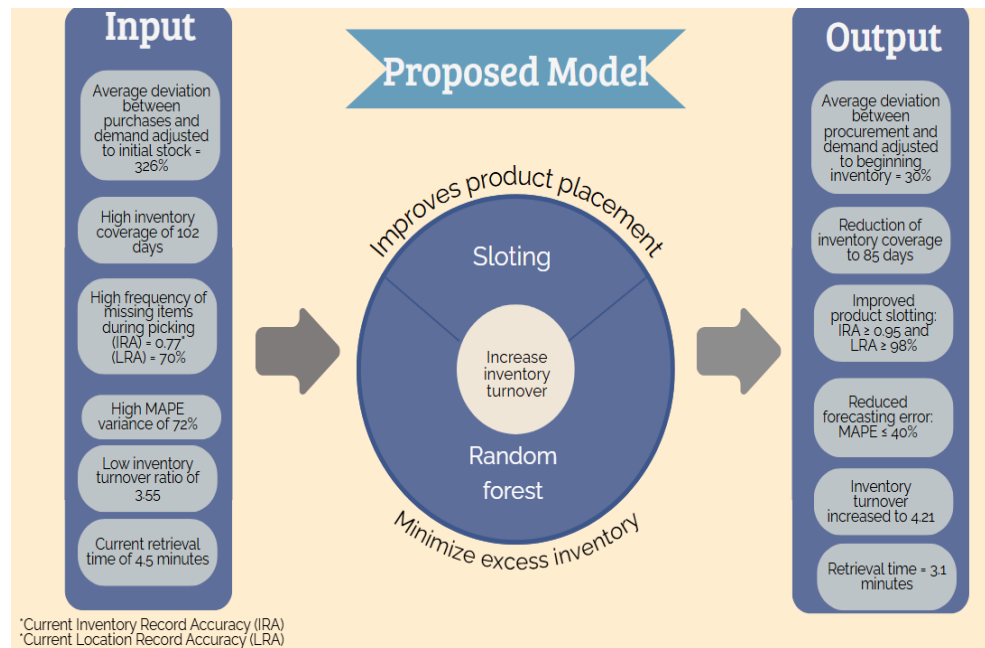


Figure 3. Macro Model of the Proposed Solution

Based on this information, a warehouse reorganization strategy was designed using slotting, assigning preferential locations to products with the highest estimated turnover in order to reduce travel distances, improve material flow, and facilitate picking operations.

The slotting technique was implemented to reorganize the physical placement of products and address the issues of disorder and operational inefficiency identified in the problem tree analysis. The primary objective was to reduce travel distance and order-picking time by assigning storage locations according to inventory turnover and access frequency.

Based on this classification, products were grouped into three categories:

- Class A, representing approximately 80% of the total annual value
- Class B, accounting for the subsequent 15%
- Class C, comprising the remaining 5%

In the location assignment strategy, the access-frequency principle was applied. Class A products were allocated to the most accessible areas closest to the dispatch zone (golden zone), whereas Class C products were relocated to more distant areas or higher storage levels (Figure 4).

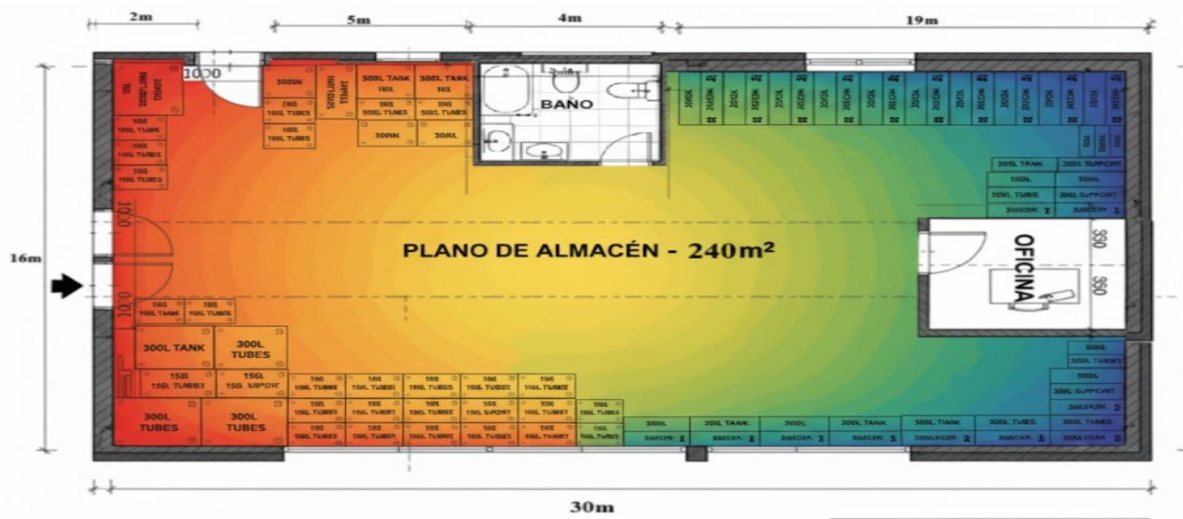


Figure 4. Slotting Heat Map

4.5 Analysis and Validation

The analysis and validation of the proposed improvement were carried out using discrete-event simulation in Arena, with the objective of evaluating the behavior of the inventory and warehouse system prior to implementation. Simulation allows representing system interactions, variability in demand, and inventory dynamics in an integrated manner. The simulation model represents the operational logic of the company through a generalized structure, which is internally replicated for all product categories (100L, 150L, 200L, 300L, and 500L). This approach ensures consistency across SKUs while avoiding redundant model representations. The system is structured around three main flows: inventory management, demand, and warehouse operations. These flows interact continuously and enable the evaluation of inventory efficiency, forecasting accuracy, and operational performance through predefined indicators. The quantitative results derived from the simulation are presented and discussed in the following section (Figure 5, Table 3).

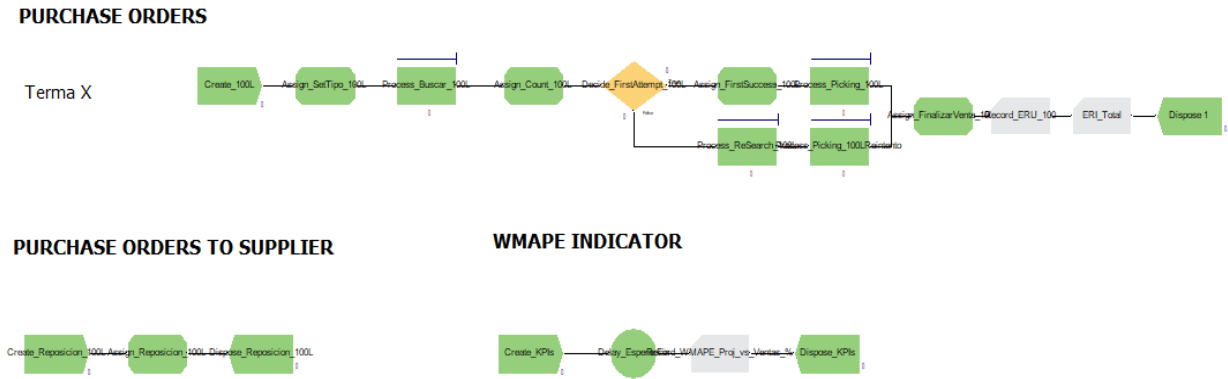


Figure 5. Arena Simulation Diagram

Table 3. Main flows, variables, and performance indicators of the simulation model

Model Flow	Purpose	Main Variables	Output / Indicator
Demand Flow	To represent stochastic demand by category	Historical sales, Min_Temp, Lag_Sales	RF Forecast, WMAPE
Inventory Flow	To simulate inflows, outflows, and replenishments	Initial stock, orders, lead time	ERU, Coverage (days)
Operational Flow	To evaluate picking performance	Layout, distance, frequency	Cycle time

5. Results and Discussion

5.1 Numerical Results

La evaluación del modelo en el set de prueba (últimas 42 semanas) demostró una capacidad superior de generalización. Se priorizó el uso del WMAPE (Weighted Mean Absolute Percentage Error) para ponderar los errores en función del volumen de ventas, asegurando una mayor precisión durante los picos estacionales de invierno, donde el riesgo de rotura de stock es crítico. To assess forecasting accuracy, performance metrics were selected to address inconsistencies reported in prior studies (Güven et al., 2021). These metrics included (Table 4):

- RMSE (Root Mean Square Error): Penalizes large deviations and is essential for minimizing the risk of stockouts.
- MAPE (Mean Absolute Percentage Error): Facilitates managerial interpretation of percentage-based forecasting errors.

Table 4. Comparison of Forecasting Error Metrics (RF vs. Baseline)

Model	RMSE	MAPE (%)	WMAPE(%)	R^2
Random Forest (To Be)	8.42	12.4%	10.8%	0.89
Moving Average (As Is)	15.60	22.5%	24.1%	0.54

To validate the physical feasibility of the model, a discrete-event simulation was developed in Arena, comparing the AS-IS scenario (empirical management) with the TO-BE scenario (RF forecasting + Slotting). The proposed scenario

incorporated projected demand volumes and operational times validated through a pilot physical relocation of SKUs as input parameters.

The simulation results (Table 5 and Table 6) reveal a substantial improvement in resource utilization. Internal efficiency (ERI) increased by 23 percentage points, while the average picking time was reduced by 20.5%, confirming that demand-based physical organization significantly streamlines the outbound flow.

Table 5. Simulation Metrics for Warehouse Operational Performance

Indicator	AS-IS Scenario	TO-BE Scenario	Variation
ERI (Internal Resource Efficiency)	75.7%	98.7%	+23.0 p.p.
ERU (200L Solar Heater)	65.96%	96.53%	+30.57 p.p.
Average Picking / Localization Time	3.9 min	3.1 min	-20.5%

The ultimate objective of the research—namely, increasing inventory turnover—was achieved by reducing the technical gap identified in the diagnostic phase. Tables 7 and 8 present the evolution of coverage and turnover for the critical SKUs (200L and 500L), which exhibited the highest levels of capital immobilization.

Table 6. Inventory Coverage for Critical SKUs (days)

SKU	Coverage AS-IS	Coverage TO-BE	Bibliographic Target	Variation (%)
200 L	105.2	87.3	86.7	-17.0%
500 L	100.3	86.9	86.7	-13.4%

Thanks to the forecasting accuracy of the RF model, safety stock levels were optimized, reducing coverage by an average of 15.2%. This adjustment enabled the Inventory Turnover Ratio (ITR) to converge toward the efficiency levels defined by the sector benchmark (4.21 turns per year).

Table 7. Evolution of Inventory Turnover (Turns/Year)

SKU	Inventory Turnover AS-IS	Inventory Turnover TO-BE	Bibliographic Target	Variation (%)
200 L	3.47	4.18	4.21	+20.5%
500 L	3.64	4.20	4.21	+15.4%

The 20.5% improvement in the turnover of the 200L SKU confirms that the integration of advanced analytics and warehouse reengineering enables SMEs in the renewable energy sector to achieve world-class operational standards, mitigating capital immobilization and maximizing the installed capacity of their logistics infrastructure.

5.2 Graphical Results

The graphical results confirm the robustness of the proposed model. Figure 5 shows strong alignment between actual and forecasted demand, achieving a WMAPE of 10.8% and effectively capturing seasonality. Variable Importance analysis (Figure 6) highlights the role of exogenous factors, such as minimum temperature and promotions, in improving performance over traditional linear models.

Operationally, the optimized layout (Figure 2) and Arena simulation (Figure 5) validate the slotting implementation, where relocating critical SKUs (200L and 500L) to high-accessibility zones reduced picking time by 20.5%. Overall, the results demonstrate consistency between demand forecasting and warehouse optimization.

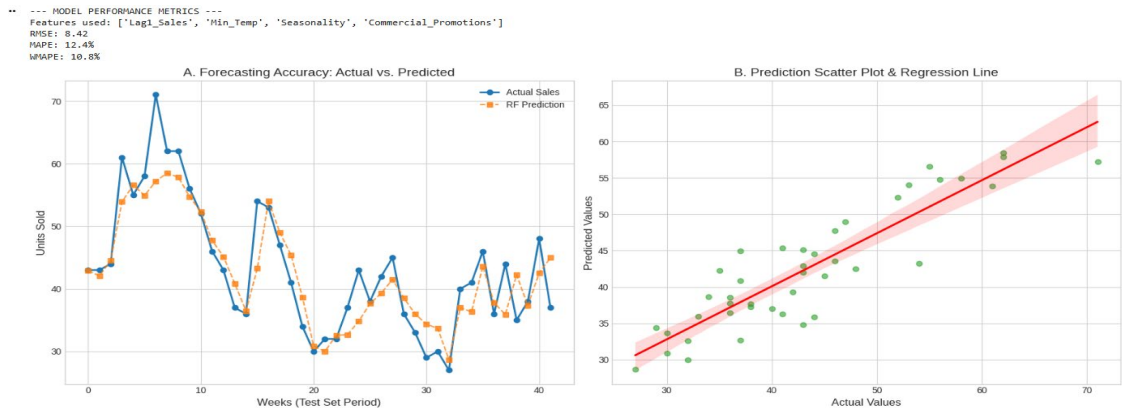


Figure 6. Comparison of actual vs. predicted sales using Random Forest

A Random Forest regression model integrating Lag-1 Sales, Minimum Temperature, Seasonality, and Commercial Promotions to optimize demand forecasting for solar water heaters, validated through WMAPE to ensure inventory reliability and scientific reproducibility.

Table 8. Ranking of Variable Importance in Forecasting

Rank	Variable	Relative Importance (%)	Impact on Demand
1	Sales (Lag-1)	60.6%	Temporal series autocorrelation
2	Minimum Temperature	26.4%	Inversely proportional (lower temperature, higher sales)
3	Seasonality	5.3%	Seasonal patterns driven by winter periods
4	Commercial	7.7%	Price elasticity detected during promotional campaigns (discounts)

5.3 Proposed Improvements

The improvement proposal is consolidated as an Integrated Decision Support System (IDSS) that links demand forecasting with warehouse operational execution. Based on the results obtained from the Random Forest model, the company transitions from an empirical purchasing scheme to a proactive replenishment approach based on four-week planning windows ($t+4$), enabling the anticipation of demand variations associated with climatic and commercial factors.

The primary improvement is reflected in the optimization of inventory levels. The reduction of forecasting error (WMAPE) to 10.8% enabled a decrease in safety stock of approximately 15%, releasing working capital without affecting service levels. This more accurate planning translates into replenishment orders aligned with actual demand, preventing recurrent overstocking.

Additionally, the implementation of a Quarterly Dynamic Slotting policy is proposed, in which the warehouse configuration adapts to the expected outbound frequency of critical SKUs. Products with higher turnover probability are strategically located in areas close to dispatch, reducing travel distances and picking times. This operational improvement directly contributes to increased logistics efficiency and to raising inventory turnover from 3.55 to 4.25 annual turns, surpassing the sector benchmark.

Finally, the category-based differentiated approach enables the application of specific inventory policies per SKU, strengthening tactical and strategic decision-making. This integrated framework ensures that the benefits of the predictive model materialize into sustainable and replicable operational improvements (Figure 7).

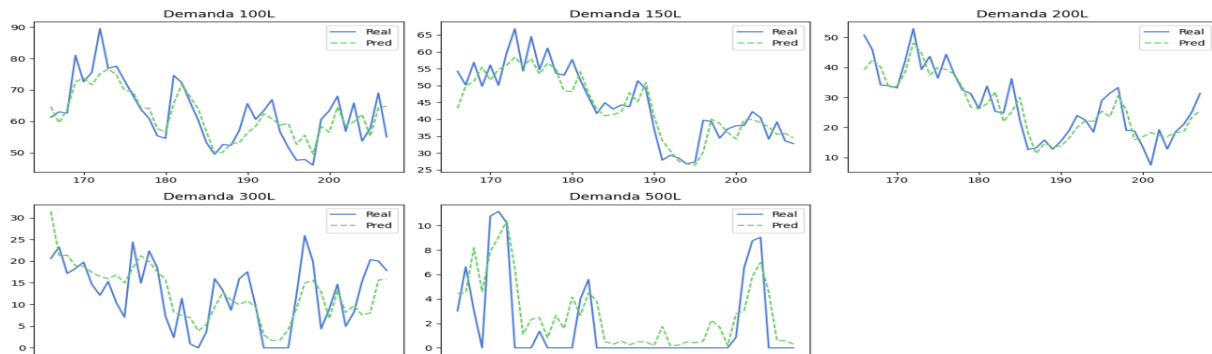


Figure 7. Predictability Charts by Category

5.4 Validation

To provide scientific validity to the obtained results, a statistical significance analysis was conducted comparing the performance of the AS-IS system with the proposed TO-BE model. A paired-sample t-test was applied to the picking cycle times obtained from the Arena simulation, establishing a null hypothesis (H_0) of equality of means and an alternative hypothesis (H_1) suggesting a significant reduction in processing time.

The results yielded a p-value of 0.0031 ($p < 0.05$), allowing the rejection of H_0 and confirming that the 20.5% reduction in processing time is statistically significant and not the result of stochastic variability within the model.

Additionally, the robustness of the predictive model was validated by comparing the residuals of the traditional forecasting approach with those of the Random Forest model. A Wilcoxon signed-rank test was applied to the absolute errors of the critical categories (200L and 500L), resulting in a Z-score of -4.12 at a 95% confidence level, confirming that the reduction of WMAPE to 10.8% represents a structural improvement in demand forecasting accuracy.

This statistical validation, together with the stability of hyperparameters in temporal cross-validation, ensures that the proposed design is capable of consistently closing the technical inventory turnover gap, increasing the ITR to 4.25 turns per year and aligning the organization with efficiency standards in the renewable energy sector.

6. Conclusion

The situational diagnosis revealed that the low inventory turnover ($ITR = 3.55$) and high coverage (102.8 days) originated from empirical demand management and an unstructured warehouse layout, generating a technical gap of 0.66 points compared to the sector benchmark of 4.21. This gap justified the need to intervene in both demand forecasting and the physical organization of the critical 200L and 500L SKUs.

To address this issue, a Random Forest-based forecasting model was developed and validated, reducing WMAPE from 24.1% to 10.8% and achieving an R^2 of 0.89. These results enabled the optimization of purchasing planning and the reduction of safety stock levels, decreasing capital immobilization without affecting service levels.

Complementarily, the slotting-based reorganization proposal, guided by the access frequency estimated by the model, reduced picking times by 20.5% and increased internal resource efficiency (ERI) to 98.7%. Overall, the integration of the predictive model and layout optimization increased inventory turnover to 4.25 turns per year, surpassing the sector benchmark.

The main contribution of this research lies in the proposal of an integrated decision support system that combines artificial intelligence and warehouse optimization, offering a replicable approach to enhance the operational competitiveness of SMEs in the renewable energy sector.

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Biographies

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