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Propuesta de Clasificación, Pronóstico de Demanda y Gestión de Inventarios para SKUs en una empresa dentro de la Industria Maderera

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**HOJA DE CALIFICACIÓN
DE TRABAJO DE FIN DE CARRERA**

Proposal for Classification, Demand Forecasting, and Inventory Management for SKUs in a Company within the Wood Industry

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RESUMEN

Actualmente, gestionar de manera eficiente la clasificación de productos, la previsión de demanda y la gestión de inventarios en las empresas representa un gran desafío, y esto también es evidente dentro de la industria de la madera. Esto se debe principalmente a la demanda volátil y a las continuas fluctuaciones del mercado, factores que exigen estrategias avanzadas para minimizar el impacto de malas gestiones en el inventario, las cuales pueden derivar en pérdidas económicas y de producto. Este estudio se enfoca en EmFALU Cía. Ltda., una empresa ecuatoriana dedicada a la fabricación de productos derivados de la madera, la cual enfrenta dificultades en la gestión de su inventario debido a la naturaleza personalizada de sus productos y a la irregularidad en los pedidos. El presente estudio analiza el impacto de estas variables en la operación de la empresa y propone soluciones basadas en técnicas avanzadas de previsión y clasificación de productos.

Para ello, se emplearon metodologías que incluyen modelos predictivos para analizar la demanda, tal como la clasificación ABC de productos según su importancia económica, y técnicas como el método de Syntetos-Boylan y la winsorización para gestionar datos atípicos y mejorar la precisión de las predicciones. Los resultados de este análisis indican que aproximadamente el 80% de la rentabilidad de la empresa proviene de un pequeño grupo de productos, lo que subraya la importancia de focalizar los recursos en la gestión eficiente de estos artículos clave. Además, se sugiere la implementación del modelo QR para optimizar la gestión de inventarios, excepto en productos de demanda con datos cero y alta variabilidad, donde sería conveniente el uso de modelos híbridos o inteligencia artificial para mejorar la capacidad predictiva.

Palabras clave: gestión de inventarios, pronósticos, industria de la madera, clasificación Syntetos- Boylan.

ABSTRACT

Efficiently managing product classification, demand forecasting, and inventory management in companies represents a significant challenge, which is also evident in the wood industry. This is mainly due to volatile demand and continuous market fluctuations, factors that require advanced strategies to minimize the impact of poor inventory management, which can lead to economic and product losses. This study focuses on EmFALU Cía. Ltda., an Ecuadorian company dedicated to manufacturing wood-derived products, which faces challenges in inventory management due to the customized nature of its products and the irregularity of orders.

This study analyzes the impact of these variables on the company's operations and proposes solutions based on advanced forecasting and product classification techniques. To achieve this, methodologies were employed that include predictive models to analyze demand, such as ABC classification of products based on their economic importance, and techniques like the Syntetos-Boylan method and winsorization to handle outlier data and improve prediction accuracy.

The results of this analysis indicate that approximately 80% of the company’s profitability comes from a small group of products, highlighting the importance of focusing resources on the efficient management of these key items. Additionally, the implementation of the QR model is suggested to optimize inventory management, except for products with zero-demand data and high variability, where the use of hybrid models or artificial intelligence would be advisable to enhance predictive capabilities.

The findings of this analysis demonstrate that adopting these techniques not only increases forecasting accuracy but also optimizes inventory management, reduces operational costs, and improves the company’s adaptability to market fluctuations.

Key words: inventory management, forecasting, wood industry, Syntetos-Boylan classification.

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1. Introduction

Efficient inventory management is a key challenge for the global timber industry, where maintaining optimal stock levels, controlling costs, and ensuring customer satisfaction are critical in a competitive market (Mishbah et al., 2019).

SMEs in manufacturing hubs like Jepara, Indonesia, are especially vulnerable to demand management issues in furniture production, frequently facing overproduction or underproduction, which increases costs and reduces competitiveness (Mishbah et al., 2019). Advanced demand forecasting techniques, such as the Winter's Model, have been shown to enhance forecast accuracy, reduce excess inventory, improve production planning, and increase customer satisfaction by aligning production with demand (Mishbah et al., 2019).

In Ecuador, the timber industry contributes 3.2% to GDP, with exports growing by 7% in 2021, totaling $503 million (El Oficial, 2022). The sector employs over 100,000 people directly and an additional 250,000 indirectly (AIMA, 2022). Ecuador's forest resources, covering 5.7 million hectares, are increasingly managed sustainably, with over 50,000 hectares certified under international standards (Castillo Vizuete et al., 2023).

Despite these resources, inventory management remains a challenge, requiring companies to balance demand with resource availability while minimizing environmental impact (Mishbah et al., 2019). EmFALU Cía. Ltda., a leading Ecuadorian wood products manufacturer, faces issues in predicting raw material and service demand, leading to overstocking and stockouts where these inefficiencies result in average annual losses of $10,000 in storage costs and missing revenue opportunities of $26,421.55 due to stockouts.

Adopting advanced forecasting techniques, as recommended by Mishbah et al. (2019), is critical for EmFALU to enhance operational efficiency and reduce costs. This study applies predictive models to analyze demand patterns, employing Pareto analysis and advanced inventory management strategies to avoid excess inventory and stockouts, ultimately optimizing profitability.

The study is structured as follows: Section 2 reviews relevant literature, including methodologies for demand classification and forecasting. Section 3 outlines the study's methodology, detailing demand analysis and forecasting processes. Section 4 presents the case study of EmFALU, highlighting applied methods and results. Section 5 discusses limitations, while Section 6 concludes with recommendations for future research and practical applications.

2. Literature review

This section explores advanced techniques for optimizing inventory management and demand forecasting in contexts with irregular and intermittent demand, such as the timber industry. Key concepts include ABC classification, which prioritizes inventory resources, and demand classification, which categorizes patterns into smooth, erratic, intermittent, and lumpy, each requiring tailored forecasting approaches. Methods like the Syntetos-Boylan Classification (SBC) and winsorization are highlighted for managing unpredictable demands and mitigating outliers to improve forecasting accuracy. Additionally, iterative calculations of reorder points (Q and R) and hybrid strategies for lumpy demand are presented. These methodologies are applied within Ecuador's timber industry, where companies like EmFALU balance resource sustainability with market fluctuations to optimize costs and ensure product availability.

2.1 ABC Classification

Demand forecasting and inventory management in contexts with intermittent or irregular demand patterns pose significant challenges, requiring specialized techniques beyond traditional methods (Boylan et al., 2008). A key approach in inventory management is the ABC classification, which organizes inventory items based on their relative importance, often using criteria such as annual dollar volume (Boylan et al., 2008). As outlined by Syntetos & Boylan

(2008), this system divides inventory into three categories: A (most important), B (moderately important), and C (least important). This enables businesses to prioritize resources and attention on A items, which are critical for operations, reducing stockouts and optimizing inventory levels (Boylan et al., 2008).

At EmFALU, focusing on category A items streamlined inventory processes and reduced unnecessary stock, improving resource allocation for critical inventory. Li et al. (2016) further highlights the benefits of integrating smart inventory systems with ABC classification, advocating for real-time demand tracking and automated inventory controls. This approach enhances responsiveness to demand fluctuations, particularly for high-priority A items, enabling a more adaptive supply chain in dynamic markets (Boylan et al., 2008).

2.2 Demand Classification

Demand can be classified as smooth, erratic, intermittent, or lumpy based on its variability and frequency, each requiring tailored forecasting techniques (Syntetos et al., 2005). Smooth demand exhibits consistent levels with low variability, while erratic demand fluctuates unpredictably. Intermittent demand shows sporadic occurrences with long intervals, and lumpy demand combines sporadic patterns with large variations, complicating accurate predictions (Boylan et al., 2008).

2.3 Syntetos-Boylan Classification (SBC)

To address the challenges posed by erratic and intermittent demand, specialized forecasting methods have been developed. A notable improvement in this area is the Syntetos-Boylan Classification (SBC). As proposed by Syntetos and Boylan(2005), the SBA separates demand size estimation from the interval estimation between demands, applying exponential smoothing to each and incorporating a correction factor to reduce errors. This method has proven effective in managing intermittent demand, especially for items with lumpy or erratic demand patterns, by providing accurate forecasts that reduce excess inventory and stockouts (Syntetos et al., 2005).

The SBC method uses two key indicators: the Average Demand Interval (ADI) and the Squared Coefficient of Variation of Demand (CV^2) (Boylan et al., 2008). Based on these indicators, the products were classified into four categories:

1. **Erratic** (ADI < 1.32, CV^2 > 0.49) High variability in demand size with relatively frequent demand.
2. **Smooth** (ADI < 1.32, CV^2 < 0.49) Low variability and frequent demand.
3. **Intermittent** (ADI > 1.32, CV^2 < 0.49) Low variability in demand size but with infrequent demand.
4. **Lumpy** (ADI > 1.32, CV^2 > 0.49) High variability and infrequent demand.

2.3.1 Average Demand Interval (ADI)

The ADI measures the average time interval between non-zero demand occurrences and is calculated by:

$$ADI = \frac{T}{N} \tag{1}$$

T = Total time considered (months)
N = Number of non-zero demand occurrences during that time

A higher ADI suggests infrequent demand, typical of intermittent or lumpy demand patterns, then a lower ADI indicates more frequent demand, characteristic of erratic or smooth demand patterns. (Boylan et al., 2008)

2.3.2 Coefficient of Variation (CV^2)

The coefficient of variation is a measure of the relative variability of demand size and is calculated as:

$$CV^2 = \left(\frac{\sigma}{\mu}\right)^2 \tag{2}$$

σ = Standard deviation of demand size
μ = Mean demand size

A higher CV^2 suggests greater variability in demand size, often associated with erratic or lumpy demand then a lower CV^2 indicates more consistent demand sizes, typical of smooth or intermittent demand patterns. (Boylan et al., 2008)

2.4 Managing Outliers with Winsorization

Boudt et al. (2020) recommend upper end winsorization with a 95th percentile threshold (upper percentile = 0.95), replacing values above this threshold with the 95th percentile value. This approach maintains data integrity while reducing the impact of extreme outliers. Winsorization is applied only to the upper bound, leaving lower values intact to preserve valid occurrences like zero demand, which often reflect seasonality or low-demand phases. Modifying such values could distort the dataset and reduce its representativeness (Boudt et al., 2020).

Extreme outliers, such as those caused by promotions or seasonal peaks, often reduce the accuracy of traditional forecasting models. Rennie et al. (2021) identified upper winsorization as an effective way to manage these outliers by capping high values without discarding spikes, maintaining dataset reliability. Braglia et al. (2019) further demonstrated its value in manufacturing industries with erratic demand, where it stabilizes demand data, mitigating volatility caused by external factors. By reducing the influence of rare events, upper winsorization improves the accuracy and reliability of forecasting models, making it a practical tool for industries prone to demand variability (Rennie et al., 2021).

2.5 Prediction Methods

The utility of interval prediction methods is increasingly recognized for managing volatile demand. Hong et al. (2023) demonstrates how combining interval forecasting with upper winsorization enables better handling of demand variability, particularly in industries like spare parts coordination where demand is unpredictable.

2.5.1 Error

For the evaluation and selection of our forecasting models, it is suggested to use Mean Absolute Percentage Error (MAPE) as the primary criterion. This is a measure widely used in forecasting practice due to its interpretability and ease of calculation and it is expressed as a percentage and measures the average magnitude of forecast errors in relative terms (Kim & Kim, 2016). The MAPE formula is defined as:

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \cdot 100\%}{n} \quad (3)$$

Formula (3) where A_i represents the actual value, F_i the forecasted value, and n the number of periods. Kim and Kim(2016) point out that MAPE is particularly useful for comparing the performance of different forecasting models, especially when dealing with time series of different scales or units. Additionally, its expression in percentage terms facilitates the communication of results to non-specialists, making it valuable in business environments.

2.5.2 Smooth Category

For SKUs classified as smooth, characterized by constant and predictable demand, we will apply three main methods:

2.5.2.1 Simple Exponential Smoothing:

Simple Exponential Smoothing is a method that assigns exponentially decreasing weights to past observations (Petropoulos et al., 2019). The formula we will use is:

$$F_{i+1} = \alpha D_i + (1 - \alpha) F_i \quad (4)$$

Formula (4) where F_{i+1} is the forecast for the next period, α is the smoothing factor (0 < α < 1), $D_i$is the actual demand in period t, and $F_i$is the forecast for period t. In this method, the parameter α determines the rate of decay of the weights. A high α gives more weight to recent observations, making the model respond quickly to changes, while a low α gives more weight to past observations, which means historical information, producing more stable forecasts(Petropoulos et al., 2019). Within this category, an alpha optimizer is used that oscillates between 0.3 and 0.6, as Petropoulos et al. (2019) note that, in many practical cases, α values in the range of 0.3 to 0.6 can provide more accurate forecasts, especially in dynamic business environments where the ability to adapt quickly to changes in demand patterns is crucial.

Recent studies, such as that of Petropoulos et al. (2019) have reaffirmed the effectiveness of Simple Exponential Smoothing for time series with stable demand patterns, typical of the smooth category we have identified in our dataset.

2.5.2.2 Moving Average

The Moving Average is a method that calculates the forecast as the arithmetic means of the n most recent observations (Stevenson, 2018). The formula we will employ is:

$$F_{i+1} = \frac{(D_i + D_{i-1} + \ldots + D_{i-n+1})}{n} \tag{5}$$

Formula (5) where n is the number of periods considered. The choice of the value of *n* is crucial in this method. A larger n will produce smoother but less reactive forecasts, while a smaller n will be more sensitive to recent changes, making it a forecast that gives relevance to the most current information. This will allow us to adjust the sensitivity of the model according to the specific characteristics of each SKU within the smooth category (Sebatjane & Adetunji, 2019).

Although it is a classic method, recent research such as that of Sebatjane & Adetunji(2019) has shown that the Moving Average remains relevant and effective for products with smooth demand. For this case, n=3 is fixed due to the trend observed in the time series and due to the period of existence of all the products to which this model is applied. Stevenson (2018) affirms that the use of n between 3 and 5 is widely used in different industries and has yielded reliable results.

2.5.2.3 Holt-Winters Method

The Holt-Winters method, also known as Triple Exponential Smoothing, is a more complex technique that decomposes the time series into three components: level, trend, and seasonality (Spiliotis et al., 2019). The formulas we will apply are:

$$Level\colon\ L_i = \alpha\left(\frac{D_i}{S_{t-s}}\right) + (1-\alpha)(L_{i-1} + T_{i-1}) \tag{6}$$

$$Trend\colon\ T_i = \beta(L_i - L_{i-1}) + (1-\beta)(T_{i-1}) \tag{7}$$

$$Seasonality\colon\ S_i = \gamma\left(\frac{D_i}{L_i}\right) + (1-\gamma)(S_{i-s}) \tag{8}$$

$$Forecast\ for\ period\ m\colon\ F_{i+m} = L_i + (m \cdot T_i) + S_{i+m-s} \tag{9}$$

Formula (7) where L_i is the level of the series, T_i is the trend, S_i is the seasonal component, and α, β, and γ are smoothing parameters and s is the stational period.
In this method, each component is updated independently in each period using its own smoothing parameter (α, β, γ). This feature makes the Holt-Winters method particularly valuable for SKUs with smooth demand that exhibit seasonal patterns or trends (Spiliotis et al., 2019).

2.5.3 Intermittent Category

For SKUs classified as intermittent we will apply the following methods:

2.5.3.1 Exponential Smoothing:

For intermittent demand, exponential smoothing is usually used in the same manner as previously described, with the consideration of an updated alpha value optimized between 0,3 and 0,6 (Nikolopoulos et al., 2011).

Babai et al. (2019) have explored modern uses of Exponential Smoothing for intermittent demand, demonstrating that it can be effective in certain contexts of moderate intermittency, such as those we have identified in our dataset.

2.5.3.2 SBA (Syntetos-Boylan Approximation):

The SBA is a modification of Croston's method designed specifically for intermittent demand-. The formula we will employ is:

$$Z_i = \alpha D_i + (1 - \alpha) Z_{i-1} \tag{10}$$

$$P_i = \alpha Q + (1 - a) P_{i-1} \tag{11}$$

$$F_i = \left(1 - \frac{\alpha}{2}\right) \cdot \left(\frac{Z_i}{P_i}\right) \tag{12}$$

In (10), where $Z_i$is the estimate of demand size and $P_i$is the estimate of the interval between demands and Q is the value between two periods where demand is not null.

This method separates the estimation of demand size (Z_i) from the estimation of the interval between demands (P_i). The factor $\left(1 - \frac{\alpha}{2}\right)$ is a correction that reduces the bias inherent in Croston's original method. This separation allows the SBA to effectively manage long periods without demand, while providing accurate estimates of when demand occurs. Similarly, the alpha used is optimized in a range of 0.3 to 0.6, to neither under-fit nor over-fit the model (Syntetos & Boylan, 2005).

Nikolopoulos et al. (2011) have confirmed the superiority of SBA over traditional methods in intermittent demand conditions, especially in complex demand contexts such as the one being analyzed.

2.5.4 Erratic Category

For SKUs classified as erratic, with low ADI but high CV^2, we will apply the following methods:

2..5.4.1 Croston's Method

Croston's method is a technique that separates the time series into two components: the size of demand when it occurs and the interval between demands (Kourentzes et al., 2017). The formulas we will use are:

$$Z_i = \alpha D_i + (1-\alpha)Z_{i-1} \tag{13}$$

$$P_i = \alpha Q + (1-\alpha)P_{i-1} \tag{14}$$

$$F_i = \frac{Z_i}{P_i} \tag{15}$$

Formula (13) where $Z_i$is the estimate of demand size, P_i is the estimate of the interval between demands, and Q is the interval between the last and current demand. In this method, each component is updated independently using exponential smoothing. The final forecast is calculated as the ratio between these two components. This separation allows Croston's method to oversee high variability in the quantity demanded, while considering the frequency of demand (Kourentzes et al., 2017).

Although it is a classic method, recent studies such as Kourentzes et al. (2017) have proposed improvements and adaptations of Croston's method to address modern challenges of erratic demand. One of these improvements is the optimization of the alpha value with respect to MAPE, which ranges between 0.3 and 0.5. As Kourentzes (2014) indicates, the establishment of low alphas is common in forecasting applications with Croston; however, higher values such as 0.6 may fit better, giving more weight to the intermittent period and the demand of the previous period.

2.5.4.2 SBA (applied to erratic demand)

The SBA method, as described earlier, also erratic demand. Although SBA was originally designed for intermittent demand, it has been found to be effective for erratic demand as well. In this context, SBA helps manage the high variability in the quantity demanded (characteristic of erratic demand) while maintaining the structure of separation between demand size and interval between demands (Babai et al., 2022).

The application of SBA to SKUs with erratic demand will allow us to compare its performance with the original Croston method and evaluate which provides more accurate forecasts in this specific context. Babai et al. (2022) have explored the application of SBA in various contexts of erratic demand, confirming its effectiveness compared to other methods.

2.5.5 Lumpy Category

The demand category classified as "lumpy", characterized by infrequent occurrences and highly variable quantities (Syntetos & Boylan, 2005). For this category the SBA was implemented, besides it’s too difficult to predict.

2.5.5.1 SBA (Syntetos-Boylan Approximation)

The Syntetos-Boylan Approximation (SBA) model was selected for forecast generation. This choice is based on a study by Syntetos et al. (2005), who demonstrated that SBA consistently outperforms other methods, such as the original Croston's method and simple exponential smoothing, in handling lumpy demand patterns. The authors evidence that SBA is particularly effective in reducing the forecast bias inherent to these erratic patterns, providing more accurate and reliable estimates for inventory planning and supply chain management in intermittent demand contexts (Syntetos et al., 2005).

2.6 Calculate Q and R

The calculation of the optimal Q (order quantity) and R (reorder point) values is performed using an iterative approach based on the model (Braglia et al., 2019). The following are the main steps and formulas used in the code:

Calculation of the order quantity Q_0: The initial order quantity is calculated using the classical Economic Order Quantity (EOQ) formula:

$$Q_0 = \sqrt{\frac{2\lambda K}{h}} \tag{16}$$

Where,

K is the ordering cost per order.
h is the holding cost per unit per day.
λ is the daily demand.

Calculation of the reorder point R: The reorder point R is adjusted by considering the average demand during lead time μ and the standard deviation σ, according to the formula:

$$R = \mu + (z \cdot \delta) \tag{17}$$

Formula (17) where z is the critical value from the standard normal distribution, calculated using the inverse cumulative probability function.

Iteration to adjust Q and R: The code iteratively adjusts Q and R until convergence. In each iteration, Q is recalculated using:

$$Q = \sqrt{\frac{2\lambda\big(K + p \cdot n(R)\big)}{h}} \tag{18}$$

$$n(R) = \sigma \cdot L(z) \tag{19}$$

Formula (19) where *n(R)* adjusts the safety stock based on demand variability, calculated as:

$$Ss = (\lambda + \sigma) * \tau * service\_level \tag{20}$$

If the values of Q and R converge (i.e., the difference between iterations is below a set tolerance threshold), the final values are rounded and used as the optimal values.

2.7 Timber Industry Context

The timber industry is a key pillar of the global economy, significantly contributing to employment, trade, and industrial growth. It includes activities ranging from raw timber harvesting to producing high-value goods like furniture, construction materials, and paper (Castillo Vizuete et al., 2023). Globally, it generates billions in revenue and supports millions of jobs, especially in rural and forested areas. As a renewable resource, sustainably managed wood is essential for transitioning to greener economies.

EmFALU Cía. Ltda., a leading company in Ecuador's timber industry, specializes in producing quality boards, shelving, and custom furniture. Effective inventory management is crucial for EmFALU to balance resource availability with fluctuating market demand, reduce waste, and maximize resource utilization. Accurate demand forecasting and classification strategies, as discussed in this study, are vital for optimizing inventory, cutting costs, and responding efficiently to market conditions.

Demand forecasting and inventory management are indispensable for the timber sector. Forecasting helps anticipate market needs and adjust production levels, minimizing risks of overproduction or stockouts. Inventory management ensures the availability of raw materials and finished goods in the right quantities at the right time, enhancing efficiency and customer satisfaction. Together, these strategies provide financial benefits and promote sustainable resource use, aligning operations with both economic and environmental goals (El Oficial, 2022).

3. Methodology

The methodology chosen to address the inventory management challenges at EmFALU Cia. Ltda. rests on three fundamental pillars: demand analysis, product classification, and forecasting and inventory management. These pillars are supported by advanced inventory control techniques aimed at reducing costs, improving forecasting accuracy, and ensuring product availability (Toro & Bastidas, 2011).

According to Toro and Bastidas (2011), the methodology for inventory control and management in an industrial enterprise should follow these three steps:

1. **Demand Analysis:**

   The demand analysis seeks to identify behavioral patterns over time, such as trends, seasonality, and cycles, which are essential for effective inventory management.

2. **Product Classification:**

   Product classification in this case is based on the Syntetos-Boylan classification method (SBC), which groups products according to the nature of their demand: Soft

Demand, Erratic Demand, Intermittent Demand, and Lumpy Demand (Syntetos & Boylan, 2005). This classification allows the inventory strategy to be optimized according to the specific characteristics of each type of demand.

3. **Forecasting and Inventory Management:**

Different forecasting methods are evaluated for each demand category. The Q-R inventory management model is adapted to each product, using the best available forecast to optimize inventory control (Braglia et al., 2019).

3. 1. Demand Analysis

The first stage of the methodology focuses on demand analysis, aiming to identify demand patterns over time by considering factors such as trends, seasonality, and cycles. These elements are critical for making accurate sales forecasts, allowing the company to adjust inventory levels according to expected demand. This analysis relies on decomposing historical demand data into key components, such as trends (indicating whether demand is consistently increasing or decreasing) and seasonality (periodic fluctuations). Understanding these fluctuations is essential for making informed decisions about inventory management, ensuring that key products are available when needed most (Toro & Bastidas, 2011).

3. 2. Product Classification using the Syntetos-Boylan Method

Once the demand is analyzed, the next step is product classification. This method is particularly useful for products with low rotation or irregular demand patterns, which require special attention to avoid overstocking or stockouts (Toro & Bastidas, 2011).

Product classification follows a multicriteria ABC approach (Li et al., 2016), dividing products into three categories based on their strategic importance:

- Class A: High-importance products that significantly impact the company's profitability. These products require more frequent and rigorous management.
- Class B: Moderately important products, which still need ongoing monitoring but less attention than Class A items.
- Class C: Lower-priority products that require less frequent review and can be managed more flexibly.

3.3. Forecasting and Inventory Management

Once products have been classified, the next phase focuses on forecasting and inventory management, applying different forecasting models based on the demand category for each product.

The accuracy of these forecasts is measured using the MAPE which allows the comparison of forecasts against actual results, adjusting strategies according to the level of error, this ensures that the most suitable forecasting models are selected for each type of demand, improving inventory planning precision (Kim & Kim, 2016).

For effective inventory management the (Q, r) control system, which is well-suited to environments with variable demand. This system defines a reorder point (r) that triggers a new order of a fixed quantity (Q) when inventory falls below this level.

The (Q, r) system is based on two key parameters:

1. Q (Order quantity): The fixed quantity to be ordered each time inventory reaches the reorder point.
2. r (Reorder point): The inventory level at which a new order is placed, determined based on expected demand during the lead time.

4. Case of Study – EmFALU

EmFALU Cía. Ltda., established in 2000, is an Ecuadorian company providing comprehensive services to the construction sector, specializing in high-quality, tailored solutions. Renowned for its production of customized boards and shelves made from premium materials, EmFALU caters to a diverse clientele, including designers, architects, and individuals seeking innovative, personalized solutions for residential or office spaces. With operations in the Triángulo de San Rafael and Sangolquí, the company strategically manages its inventory and production to meet client demands. However, challenges arise in inventory management, particularly in handling raw materials across two warehouses, due to demand variability and the customization of its products.

As reported by EmFALU (2024), the company excels in designing and manufacturing furniture, with a focus on products like boards and edges, which are central to this study. Its customers range from professionals like designers and architects to individuals aiming to enhance their spaces. EmFALU offers a variety of products and services that streamline the furniture design, manufacturing, and installation processes, emphasizing personalized solutions and specialized attention. Key services include precise board cutting and laminating or edging, both of which are highly relevant to the research at hand.

4.1 Demand Analysis

However, EmFALU faces a problem with inventory management. The company currently manages around 934 SKUs (stock keeping unit), which include not only boards and edges but also process supplies and smaller components such as nails, screws, and hinges. These operations are managed in two main warehouses: B1, located in the Triángulo de San Rafael, and B4, in Sangolquí. To prioritize the products on which the company should focus its efforts, profitability from the previous year was used as a criterion to identify the product groups that bring the greatest benefit. This analysis is crucial for decision-making regarding inventory and production optimization.

4.1.1 SKUS product profitability

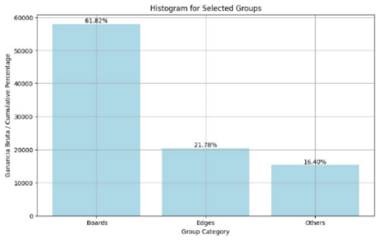


Figure 1: Histogram for Selected Groups (done by the authors)

As part of this study, a classification of EmFALU's products by categories was conducted, focusing on the groups of boards and edges, with the goal of analyzing their contribution to the company's profitability. This classification is crucial for understanding the revenue structure and guiding inventory and production management strategies more efficiently.

The analysis is presented in Figure 1, which shows the distribution of gross profit or cumulative percentage across the main product categories. The results are revealing:

- Boards: This category represents 61.82% of the total profitability, making it the largest source of income for the company.
- Edges: Contributing 21.78% to the overall profitability, this is the second most important group.
- Others: The remaining 16.40% corresponds to other product categories, like hinge or screws for the furniture.

Figure 1 clearly shows that approximately 80% (more precisely, 83.60%) of EmFALU's profitability comes from the combination of boards and edges. This finding is significant as it follows the Pareto principle or the 80/20 rule, which suggests that a small proportion of causes (in this case, product categories) are responsible for most of the effects (profitability). This classification serves as the foundation for the next steps in the study, which include a more detailed ABC analysis of the SKUs within these key categories and the application of the Syntetos-Boylan method for demand classification.

4.1.2 ABC Classification

Figure 2: Pareto chart for boards and edges (done by the authors)

Continuing with the analysis, it was conducted into the Boards and Edges categories through an ABC analysis to identify the most critical SKUs in terms of profitability. This approach allows for more precise and efficient inventory management, aligned with the economic impact of each product. The ABC classification method is widely used in practice for managing large numbers of inventory items, as noted by Teunter et al. (2010) in their study on ABC classification and inventory costs.

For Boards, the ABC analysis revealed a typical distribution, as shown in Figure 2:

- Category A: Includes 32 SKUs that generate approximately 80% of the total gross profit for the boards, with a value of $46,323.84.
- Category B: Comprises the next SKUs that contribute around an additional 15% of the gross profit, totaling $8,790.37.
- Category C: Encompasses the remaining SKUs, contributing the final 5% of the gross profit, amounting to $2,972.67.

Similarly, for Edges, the ABC analysis presented in Figure 2 showed:

- Category A: Consists of 64 SKUs that generate 80% of the gross profit in this category, totaling $16,283.61.
- Category B: Includes SKUs that account for the next 15% of the gross profit, valued at $3,102.02.

- Category C: Contains the remaining SKUs, contributing the last 5% of the gross profit, totaling $1,045.67.

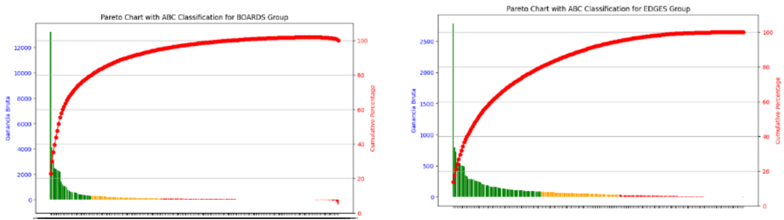


Figure 3:: Distribution for boards (done by the authors)

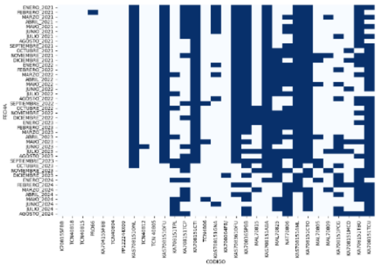
This distribution is clearly visualized in Figure 3, which shows the bar charts for the ABC classification of Boards and Edges, respectively. These charts concisely illustrate how a small proportion of SKUs (Category A) is responsible for most of the gross profit in both product categories.

The identification of these critical SKUs (32 in Boards and 64 in Edges) that generate approximately 80% of the profitability in each category allows EmFALU to focus its resources and efforts more efficiently. These products require special attention in terms of inventory control, demand forecasting, and sourcing strategies.

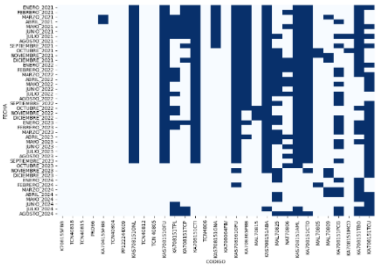
It is worth noting that while the analysis focuses on profitability, Teunter et al. (2010) propose a cost-based criterion for ABC classification that considers shortage costs, demand rates, holding costs, and order quantities. Their study demonstrates that this approach can lead to significant inventory cost savings while maintaining target service levels.

Based on this analysis, the focus will be directed towards the Category A SKUs, which play the most significant role in driving profitability. By concentrating efforts on these products, EmFALU can optimize inventory management and improve overall operational efficiency. This approach aligns with the findings of Teunter et al. (2010), who emphasize the importance of tailored inventory management strategies for different ABC categories to balance service levels and inventory costs effectively.

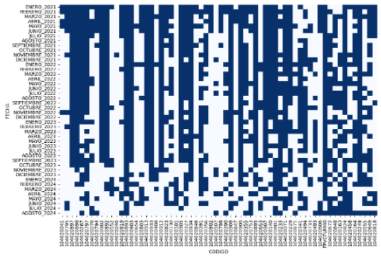
4.1.3 Syntetos-Boylan Classification (SBC)



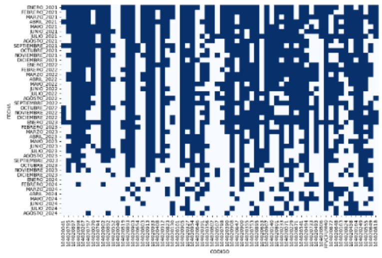
Boards B1



Boards B4



Edges B1



Edges B4

Figure 4: Demand patterns across SKUs (done by the authors)

Before the Syntetos-Boylan classification, it's important to visually capture the nature of demand patterns across the analyzed SKUs. Figure 4 presents a heat map of demand over time for each SKU, providing a clear illustration of periods of zero demand (depicted in blue) interspersed with periods of positive demand (shown in white). This visualization not only highlights the intermittent nature of demand but also underscores the frequent occurrence of zero-demand periods, which are pivotal in understanding the need for specialized forecasting techniques.

4.2 Product classification

Such irregular demand patterns, with substantial periods of no demand, set the stage for applying methods like the Syntetos-Boylan approximation, which are designed to oversee such challenges effectively.

In the next phase of the study, the classification method proposed by Syntetos et al. (2005) was implemented to categorize EmFALU's products according to their demand patterns. This classification, also used in recent comparative studies (Lukinskiy et al., 2023), is crucial for selecting appropriate forecasting strategies and optimizing inventory management. The thresholds used for classification (ADI < 1.32, CV² > 0.49) are based on the seminal work of Syntetos, A.A., Boylan, J.E., and Croston, J.D.(2005), *"On the categorization of demand patterns"* These parameters have been widely adopted in the literature and inventory management practice for classifying demand patterns. This method helps distinguish products with different demand behaviors, which is crucial for selecting the most appropriate forecasting strategy.

This classification provided a clear understanding of the demand behavior for each SKU, enabling the company to adjust its forecasting methods accordingly. Products with erratic or lumpy demand required more specialized approaches, such as the Syntetos-Boylan Approximation (SBA), to improve forecasting accuracy, while products with smooth or intermittent demand could be forecasted using traditional methods or adjusted models like SBA(Boylan et al., 2008).

The results of this analysis are presented in Figures 7 and 8, which illustrate the distribution of categories for boards and edges in warehouses B1 and B4.

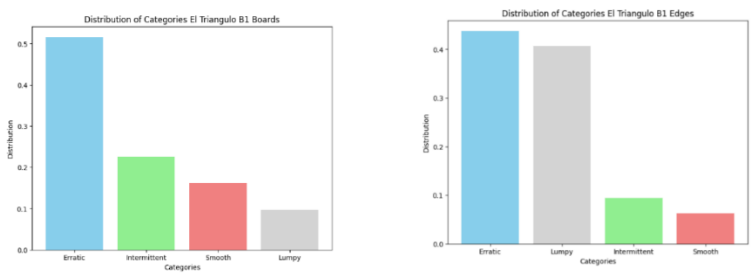


Figure 5: Distribution boards and edges B1 (done by the authors)

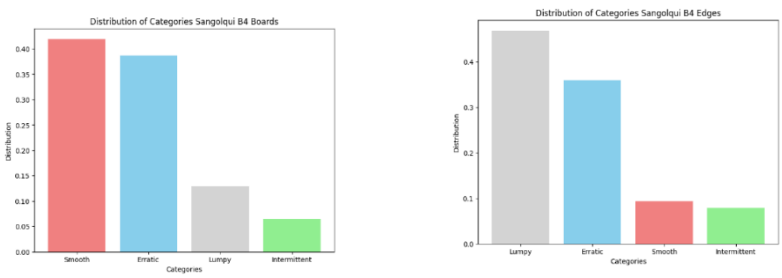


Figure 6: Distribution boards and edges B4 (done by the authors)

- Boards B1 - Figure 5: The distribution shows a predominance of erratic demand (52%), followed by intermittent (23%), smooth (16%), and lumpy (10%). This configuration suggests significant variability in the quantity demanded, but with a high frequency for most SKUs.

- Boards B4 - Figure 6: A more balanced distribution is observed between smooth demand (42%) and erratic (39%), with less presence of lumpy demand (13%) and intermittent (6%). This distribution indicates more stable demand patterns compared to B1.
- Edges B1- Figure 5: The category shows a high proportion of erratic demand (44%) and lumpy (41%), with less representation of intermittent (9%) and smooth (6%) demand. These results indicate more irregular demand patterns, which are potentially difficult to predict.
- Edges B4 - Figure 6: A predominance of lumpy demand (47%) and erratic (37%) is observed, with smaller proportions of smooth (9%) and intermittent (7%) demand. This distribution is like B1 for edges, but with more emphasis on lumpy demand.

These distributions reveal significant differences in demand patterns between the two warehouses and between the categories of boards and edges. The high proportion of SKUs with erratic and lumpy demand in both categories and warehouses suggests the need to implement specialized forecasting methods, such as the Syntetos-Boylan Approximation (SBA) (Syntetos & Boylan, 2005), to improve forecasting accuracy.

It is important to note that the classification was based on demand data starting from the first January 2021 in which each product recorded sales. This methodological approach ensures that the demand patterns analyzed reflect the actual behavior from the moment the product became relevant in the market, avoiding distortions caused by zero-demand periods before its introduction.

The implementation of differentiated forecasting and inventory management strategies based on these categories will enable EmFALU to optimize stock levels, improve customer service, and reduce costs associated with excess or stockouts. Additionally, this classification provides a solid foundation for future strategic decisions regarding supply chain management and production planning, in line with Boylan et al. (2008) recommendations for the practical application of these classification methods.

4.2.1 Winsorizing demand

The decision to apply winsorization was driven by the need to manage extremely high values without entirely removing them. As Rennie et al. (2021) point out, outliers can have a significant impact on revenue management, and it is essential to identify and manage them appropriately. In our case, winsorization allows us to retain information on significant demand spikes while limiting their extreme magnitude to prevent distortions in our forecasting models.

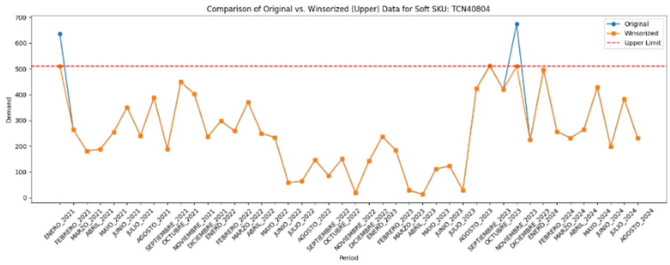


Figure 7: Comparison of Original vs. Winsorized SKU: TCN40804 (done by the authors)

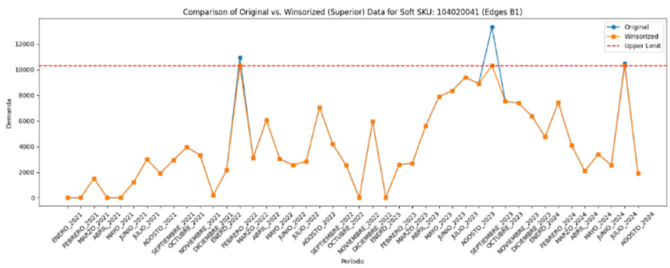


Figure 8: Comparison of Original vs. Winsorized SKU: 1040200041 (done by the authors)

The effects of winsorization can be observed in Figures 7 and 8, which illustrate its impact on two different SKUs. For SKU TCN40804 (Figure 7), several demand peaks exceeding the upper threshold are visible. Winsorization has brought these peaks down to a more manageable level while preserving the overall trend of the time series. In the case of SKU 104020041 (Figure 8), an extreme demand spike occurred in August 2023. Winsorization adjusted this outlier to the upper threshold, maintaining the information about a significant demand increase without allowing it to disproportionately distort the model. The application of winsorization in the present study has effectively reduced extreme volatility in the data, improving the stability of our forecasts.

4.3 Inventory system and management

Once products have been classified according to their demand, it is essential to use this information to generate forecasts. Singhry & Abd Rahman (2019) indicates that forecasts are the foundation of all supply chain planning. This is because when planning production, capacity, or personnel, it is necessary to know or infer about potential future occurrences to make decisions on how to act accordingly. In the context of our research, the objective is to determine the possible monthly demand to implement inventory control based on the products on which we are focusing. Therefore, inventory forecasting becomes crucial and directly applicable to our study.

4.3.1 Forecasts

Having established the type of demand and the SKUs belonging to each category, the next step is to apply specific forecasting models, validated by various authors for each case, with the purpose of evaluating the performance of each and selecting the one that presents the least error.

In this research, it was done with approximately 106 SKUs per warehouse, specifically warehouses B1 and B4. Given the considerable volume of SKUs and the need to forecast for all of them, it was chosen to standardize the forecasting models. This standardization has been implemented using Python, allowing us to efficiently automate and scale the forecasting process for all SKUs. As noted by Tadayonrad & Ndiaye (2023), the use of advanced computational tools, such as Python, for processing and analyzing large volumes of SKU data, allows for greater accuracy and efficiency in demand forecasting.

For the exemplification of model application, only the groups from warehouse B4 will be shown. It should be noted that each of the models described subsequently has been applied to each SKU belonging to each group and from both warehouses.

4.3.1.1 Application Smooth Category

Once the models to be used were defined, all SKUs belonging to this category were evaluated, with their MAPEs indicated in Annex 1. The evaluation of each SKU follows the process presented below in Figure 9.

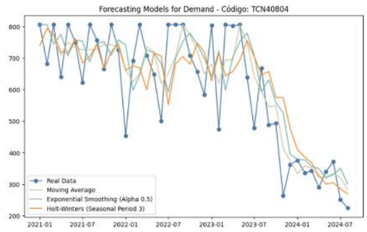


Figure 9: Forecast graphic of TCN40804 – soft, B4 (done by the authors)

The actual demand is indicated, and the forecasts generated for the three proposed models are shown. It is worth noting that for model selection, the calculated MAPE considers only the last six periods of the series. As Petropoulos et al. (2018) affirm, considering the error of the most recent periods is beneficial as it captures the most recent pattern and current performance of the forecast.

4.3.1.2 Application Intermittent Category

Using the Python tool, demand graphs were generated comparing them with the selected models for this type of demand. The evaluated MAPE error is reflected in Annex 3 for each of the SKUs belonging to this category, like the one presented below in Figure 10.

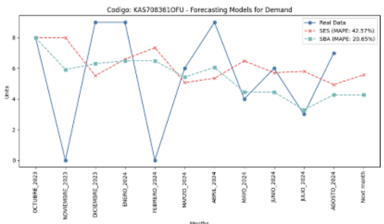


Figure 10: Forecast graphic of KAS708361OFU – intermittent, B4 (done by the authors)

As observed, the applied forecasts visually differ from the actual demand, due to the nature of the demand and the objective of the forecast, which is to smooth the difference between actual and forecast values. Appendix 1 shows the summary of the error obtained once the model generating the lowest error has been selected. It is important to mention that for the calculation of MAPE in these intermittent series, the value of 0 is replaced by 1. This is due to periods of null demand where there is a mathematical limitation in its calculation as it becomes infinite. Syntetos & Boylan (2005) establish that replacing zeros with a small or minimum value is an effective practice, to maintain the application of a widely understood metric.

4.3.1.3 Application Erratic Category

Through Python, the forecasts are incorporated and summarized in a single graph, showing the actual demand and the time series generated with the selected forecast models. This was done with all SKUs belonging to this category, and the MAPE obtained is summarized in Annex 1. Figure 11 shows one of the SKUs.

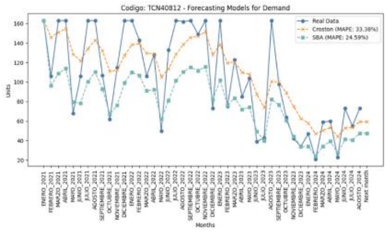


Figure 11: Forecast graphic of TCN40812– erratic, B4 (done by the authors)

Appendix 1 shows the summary table with the forecasts for warehouses B1 and B4 (edges and boards) with the selection of the best model for each SKU with respect to its MAPE.

4.3.1.4 Lumpy Category

The demand category classified as "lumpy", characterized by infrequent occurrences and highly variable quantities. For this purpose, the Python model optimizes the alpha value between 0.3 and 0.6 based on the foundations. Figure 12 shows one of the SKUs.

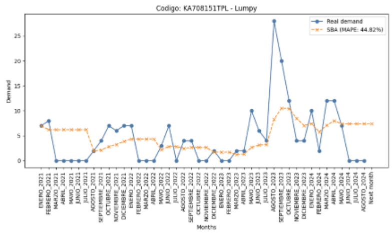


Figure 12: Forecast graphic of KA708151TPL– Lumpy, B4 (done by the authors)

4.3.2 Inventory Management

Following the demand forecasting process for SKU boards and edges at EmFALU Cía. Ltda., four demand categories were identified: smooth, erratic, intermittent, and lumpy. For the smooth, erratic, and intermittent demand categories, the Q,R inventory model was chosen, optimizing both order quantity and reorder point to ensure adequate service levels while minimizing inventory costs. However, for lumpy demand, characterized by high variability and prolonged periods of zero demand, it is impractical to apply this model due to the difficulty of accurately predicting future demand (Braglia et al., 2019).

4.3.2.1 Inventory Parameters Used

In the process of optimizing inventory management at EmFALU, several key parameters were provided by the company through calculations and approximations based on daily operations. These parameters were used to calculate the optimal order quantity (Q) and reorder point (R) in the Q,R model:

- Ordering cost *(K)*: $22.45 per order, representing the administrative and operational costs associated with placing an order for raw materials or products.
- Holding cost per day *(h):* $0.12 per unit, estimated based on storage costs, product deterioration, and warehouse space utilization.
- Stockout cost or penalty *(p):* $104.43 per unit of unsatisfied demand, including both the opportunity cost and the impact on customer satisfaction.
- Lead time (τ): 2 days, representing the estimated time from order placement to inventory availability.

- Minimum order quantity: For boards, a minimum order of 7 units was set, while for edges, the minimum was 195 meters. These values are based on the company's production and storage capacity and ensure that orders meet operational requirements.

These parameters were validated by EmFALU's operational team through historical analyses and adapted to the current market conditions (EmFALU, 2024).

4.3.2.2 Implementation of the Q,R Model

The *Q,R* model is widely used in inventory management for smooth, erratic, and intermittent demand categories, as it effectively optimizes both inventory holding costs and ordering costs while ensuring adequate service levels.

Table 1 shows the results obtained for various product codes at EmFALU, calculated using the *Q,R* model. Table 1 shows daily demand (λ), standard deviation (σ), optimal order quantity (Q), and reorder point (R):

Table 1: Inventory management for a board from B4 smooth category

SKU	Q	R	Ss
K708155FBB	73	77	54

These results demonstrate variability in order quantities and reorder points according to the characteristics of each product's demand, enabling efficient inventory management (Braglia et al., 2019). The results obtained are in appendices 4, 5 and 6 for each of the categories.

4.3.2.3 Challenges with Lumpy Demand

Lumpy demand is characterized by highly irregular patterns, with extended periods of no demand followed by unexpected spikes. This extreme variability makes it challenging to apply the *Q,R* model effectively, as traditional methods fail to capture the unpredictability of such demand. Recent studies suggest that hybrid models or artificial intelligence-based techniques, such as neural networks, are more suitable for managing this type of demand (Amirkolaii et al., 2017). These techniques can more accurately predict demand spikes and improve inventory management in uncertain conditions.

The use of the *Q,R* model for smooth, erratic, and intermittent demand categories has allowed EmFALU to optimize its inventory management, reducing costs while ensuring an adequate level of service.

5. Conclusions

The first key point is the ABC categorization applied initially. This allowed a focus on SKUs contributing the most to profitability. Specifically, we concentrated on edges and boards, identifying the most relevant SKUs within these categories to maximize economic impact and improve inventory management operations.

The Syntetos-Boylan classification provided significant clarity and ease in handling demand. This classification helped assess the complexity and critical aspects of each category (smooth, erratic, intermittent, and lumpy). The demand for boards and edges is highly variable, with most SKUs falling into erratic (high variability), intermittent (many zero-demand periods), and lumpy (high variability with many zero-demand periods) categories. These characteristics make finding suitable forecasting models challenging. Although the MAPE achieved was not optimal (10-15%), the results are practical, given the market's complexity and forecast errors ranging from 30-40%, depending on the category. Initially, the company’s forecast error was 50-60%, meaning a 20% improvement in product availability and management.

For lumpy SKUs, the Q, R model was excluded due to errors exceeding 55%. High variability and intermittency require substantial safety stock, leading to idle inventory during zero-demand periods. A "make-to-order" system is recommended, emphasizing supply chain agility to ensure quick responses, prompt supplier action, and alignment with customer waiting times (Ludeña & Sosa, 2019). While the company’s lead time is currently short (2 days), exploring customer willingness to wait is crucial for the system's success.

The proposed Q, R inventory model showed promising short-term improvements, though long-term economic impacts remain unevaluated due to limited application time. Regarding inventory levels, 76% of SKUs have higher inventory than suggested by the Q, R model. The model recommends maximum inventory levels combining safety stock and optimal order quantity Q. Comparing the company's inventory with the model, over a third of SKUs exceed suggested levels, implying reduced warehouse usage if the Q, R model is implemented, allowing greater flexibility for high-variability products.

Simulations with real company data confirmed that after five runs per SKU, 88.7% avoided stock-outs, validating the model's effectiveness in supporting dynamic demand even when built with forecasted values. This connection between forecasts and the Q, R model highlights its robustness (simulator details in Appendix 7).

While these results offer immediate inventory improvements, refining the models to daily scenarios is vital. Long-term economic impacts also require evaluation, particularly regarding the agile system's reliance on frequent supplier orders driven by demand. Assessing whether transportation costs will increase or remain manageable is essential for adjusting and optimizing the initial model.

6. Limitations

This study faced several limitations impacting the accuracy and scope of the results. One key limitation was the data periodicity, limited to monthly records. While suitable for analyzing general trends, the absence of granular data, such as weekly or daily records, restricted the ability to capture detailed demand behaviors, rapid variations, and short-term market changes, affecting prediction accuracy.

The use of monthly data also resulted in a small dataset, limiting the application of advanced machine learning techniques like deep learning or hybrid approaches, which require larger datasets for optimal performance. Consequently, potentially more accurate and adaptable models could not be fully explored or validated.

Year-to-year trends in board demand posed additional challenges due to market fluctuations. Critical boards lacked historical data prior to January 2024, limiting the ability to capture broader patterns and accurately forecast future changes, particularly given the dynamic nature of product demand.

Time constraints further influenced the study, restricting the opportunity for extensive testing and iterative parameter optimization. This limited the exploration of advanced solutions for managing intermittent and erratic demand in high-variability contexts.

The Syntetos-Boylan classification effectively categorized demand but was limited by monthly data, which could not fully capture intra-month variability. Lastly, reliance on company-provided historical data introduced bias, as it did not account for broader market trends or external factors like economic fluctuations. Incorporating external data sources and extending the study period would improve predictive reliability and scope.

7. Future studies

To strengthen and expand the findings of this study, several lines of future research are proposed. In the first place, obtaining more granular data, such as weekly or daily records, would allow capturing more detailed patterns and improving the accuracy of forecasting models. Additionally, advanced techniques, such as hybrid models that combine traditional statistical methods with artificial intelligence algorithms, could improve predictive capacity, especially for erratic and intermittent demands.

It is also recommended to explore the long-term economic impact of the proposed inventory models, assessing costs associated with more frequent orders and transportation. Specific strategies for managing lumpy demand through "make-to-order" systems should also be developed, analyzing customer willingness to wait for custom-made products.

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Appendices

Appendix1: MAPEs of edges and wood boards from B1 and B4 - Smooth

Woodboards B1 "Smooth"

SKU	Forecast	Best Model	MAPE
K708155FBB	238	Holt-Winters	14,25174887
TCN40804	268	Moving Average	23,98141888
KA708064FB/	18	Moving Average	17,95300216

Woodboards B4 "Smooth"

SKU	Forecast	Best Model	MAPE
K708155FBB	336	Moving Average	14,04329703
TCN40815	85	Holt-Winters	89,76554548
PRO66	34	Holt-Winters	31,81177902
TCN40804	256	Holt-Winters	17,20325084
PP122244X09	113	Moving Average	10,4501564
TCN 40805	140	Exponential Smoothing	24,10460583
TCN4806	25	Holt-Winters	11,66173437
KA708064FB/	16	Moving Average	20,12617013

Edges B1 "Smooth"

SKU	Forecast	Best Model	MAPE
104020041	3792	Moving Average	46,52793479
104020898	385	Holt-Winters	9,459690943
104020933	470	Holt-Winters	59,1922841
104020101	140	Holt-Winters	45,52428467

Edges B4 "Smooth"

SKU	Forecast	Best Model	MAPE
104020898	291	Holt-Winters	39,2898553
104020267	409	Moving Average	16,75020553
104020040	2035	Holt-Winters	83,81432778
104020913	120	Moving Average	8,548714693
104020900	238	Holt-Winters	40,09886221

Appendix2: MAPEs of edges and wood boards from B1 and B4 – Intermittent

Woodboards B1 “Intermittent”

SKU	Forecast	Best Model	MAPE
KA708151TPL	3	SBA	30,99
KA708151CTI	9	SES	15,97
KA708365PBB	1	SES	21,12
KAS708151ABA	5	SBA	33,23
NAT70806	2	SBA	14,53
KAS708151AML	2	SBA	10,31
KA708151CTO	2	SBA	0,38
KA708151TBO	3	SBA	12,3
KA708151TCU	0	SBA	26,7

Woodboards B4 “Intermittent”

SKU	Forecast	Best Model	MAPE
KA708151CTI	7	SBA	23,23
KAS708151AML	3	SBA	32,82
KA708151CTO	6	SBA	30,41
KAS708361OFU	4	SBA	20,65
KA708151PCG	5	SBA	26,5
KA708151TBO	4	SBA	24,83

Edges B1 “Intermittent”

SKU	Forecast	Best Model	MAPE
104020267	9	SBA	36,5
104020893	48	SBA	24,5
104020391	8	SBA	29,27
104020801	23	SBA	44,4
104020071	12	SBA	31,36
104020824	0	SBA	40,7

Edges B4 “Intermittent”

SKU	Forecast	Best Model	MAPE
104020893	54	SBA	22,05
104020356	14	SBA	36,92
104020390	282	SBA	44,26
104020233	14	SBA	31,03
104020164	8	SBA	14,55

Appendix3: MAPEs of edges and wood boards from B1 and B4 – Erratic

Woodboards B1 “Erratic”

SKU	Forecast	Best Model	MAPE
TCN40818	75	SBA	37,8
TCN40815	56	SBA	43,83

PRO66	14	SBA	33,3
KA704155FBB	10	Croston	21,97
PP122244X09	115	SBA	35,84
KAS708151ONL	18	SBA	29,08
TCN40812	14	SBA	37,91
TCN 40805	53	SBA	41,25
KAS708151OFU	9	SBA	36,43
TCN4806	5	SBA	30,05
KAS708151GNA	8	SBA	31,84
MAL70805	10	SBA	33,36
MAL70809	4	SBA	33,33
KA708151MCD	4	SBA	30,91

Woodboards B4 "Erratic"

SKU	Forecast	Best Model	MAPE
TCN40818	38	SBA	42,98
KA704155FBB	8	SBA	26,86
KAS708151ONL	27	Croston	28,23
TCN40812	47	SBA	24,59
KAS708151OFU	10	SBA	16,91
KA708151TCP	2	SBA	31,08
KAS708151GNA	16	SBA	31,51
KA708365PBB	7	SBA	38,2
MAL70815	11	SBA	30,88
MAL70805	25	SBA	40,18
MAL70809	11	SBA	33,43
KA708151MCD	12	SBA	29,63

Edges B1 "Erratic"

SKU	Forecast	Best Model	MAPE
104020795	7	SBA	43,05
104020897	921	Croston	22,42
104020794	187	SBA	41,7
104020902	539	SBA	39,41
104020892	156	SBA	37,7
104020552	52	SBA	41,28
104020040	142	SBA	35,94
104020819	45	SBA	38,29
104020654	84	SBA	44,86
104020803	104	SBA	37,95
104020913	31	SBA	29,44
104020408	210	SBA	38,51
104020912	97	SBA	37,28
104020905	59	SBA	25,76
104020934	68	SBA	29,68

104020646	38	SBA	44,03
104020802	302	SBA	46,16
104020507	160	SBA	41,13
104020798	8	SBA	39,87
104020647	47	SBA	36,25
104020900	50	SBA	26,23
104020653	25	SBA	50,33
104020907	16	SBA	31,82
104020671	29	SBA	37,75
104020733	58	SBA	37,07
104020806	96	SBA	39,06
104020249	31	SBA	26,76
104020818	23	SBA	35,1

Edges B4 "Erratic"

SKU	Forecast	**Best Model**	**MAPE**
104020041	2078	SBA	41,18
104020897	1152	Croston	31,45
104020794	205	SBA	46,56
104020902	273	SBA	25
104020892	384	SBA	30,82
104020552	53	SBA	33,88
104020903	11	SBA	31,87
104020654	19	SBA	35,26
104020803	76	SBA	37,98
104020933	341	SBA	34,44
104020408	291	SBA	44,64
104020912	260	SBA	35,04
104020130	496	SBA	42,78
104020101	37	SBA	41,73
104020905	54	SBA	32,21
104020802	644	SBA	30,69
104020507	284	SBA	45,91
104020798	50	SBA	41,37
104020895	106	SBA	21,74
104020907	71	SBA	32,72
104020806	12	SBA	35,41
104020249	111	SBA	35,05
104020818	79	SBA	36,52

Appendix4: Q R of edges and wood boards from B1 and B4 – Smooth

Woodboards B1 "Smooth"

SKU	**Q**	**R**	**SS**
K708155FBB	74	85	62
KA708064FB/	13	5	4

TCN40804	68	86	68

Woodboards B4 "Smooth"

SKU	Q	R	SS
K708155FBB	73	77	54
KA708064FB/	15	5	4
PP122244X09	39	63	60
PRO66	23	10	7
TCN 40805	42	54	48
TCN40804	76	121	102
TCN40815	48	59	51
TCN4806	19	8	6

Edges B1 "Smooth"

SKU	Q	R	SS
104020041	480	1853	1600
104020101	195	79	65
104020898	195	69	43
104020933	195	86	55

Edges B4 "Smooth"

SKU	Q	R	SS
104020040	195	534	458
104020267	195	116	89
104020898	195	61	42
104020900	195	35	19
104020913	195	22	14

Appendix5: Q R of edges and wood boards from B1 and B4 – Erratic

Woodboards B1 "Erratic"

SKU	Q	R	SS
KA704155FBB	12	5	4
KA708151MCD	8	3	3
KAS708151GNA	11	4	3
KAS708151OFU	12	4	3
KAS708151ONL	16	6	5
MAL70805	13	6	5
MAL70809	8	4	4
PP122244X09	45	47	39
PRO66	15	8	7
TCN 40805	30	27	23
TCN40812	18	18	17
TCN40815	31	27	23
TCN40818	37	40	35
TCN4806	9	4	4

Woodboards B4 “Erratic”

SKU	Q	R	SS
KA704155FBB	11	4	3
KA708151MCD	13	4	3
KA708151TCP	7	2	2
KA708365PBB	11	6	6
KAS708151GNA	15	6	5
KAS708151OFU	12	6	5
KAS708151ONL	20	8	6
MAL70805	20	12	10
MAL70809	13	8	7
MAL70815	13	5	4
TCN40812	32	39	36
TCN40818	53	91	88

Edges B1 “Erratic”

SKU	Q	R	SS
104020040	195	79	70
104020249	195	5	3
104020408	195	409	395
104020507	195	151	140
104020552	195	25	22
104020646	195	42	39
104020647	195	79	76
104020653	195	13	11
104020654	195	66	60
104020671	195	27	25
104020733	195	21	17
104020794	195	87	75
104020795	195	29	29
104020798	195	46	47
104020802	195	202	182
104020803	195	44	37
104020806	195	224	218
104020818	195	23	21
104020819	195	21	18
104020892	195	115	105
104020897	195	296	235
104020900	195	10	7
104020902	195	359	323
104020905	195	19	15
104020907	195	3	2
104020912	195	56	50
104020913	195	12	10
104020934	195	14	9

Edges B4 “Erratic”

SKU	Q	R	SS
104020041	363	1276	1137
104020101	195	34	32
104020130	195	310	277
104020249	195	25	18
104020408	195	231	212
104020507	195	169	150
104020552	195	21	17
104020654	195	7	6
104020794	195	134	120
104020798	195	102	99
104020802	195	299	256
104020803	195	31	26
104020818	195	65	60
104020892	195	137	111
104020895	195	25	18
104020897	195	407	330
104020902	195	214	196
104020903	195	-1	-2
104020905	195	55	51
104020907	195	30	25
104020912	195	101	84
104020933	195	140	117

Appendix6: Q R of edges and wood boards from B1 and B4 – Intermittent

Woodboards B1 "Intermittent"

SKU	Q	R	SS
KA708151CTI	11	2	1
KA708151CTO	7	0	0
KA708151TBO	7	1	1
KA708151TPL	7	2	2
KA708365PBB	7	0	0
KAS708151ABA	8	1	1
KAS708151AML	7	0	0
NAT70806	7	3	3

Woodboards B4 "Intermittent"

SKU	Q	R	SS
KA708151CTI	10	2	2
KA708151CTO	9	1	1
KA708151PCG	8	2	2
KA708151TBO	7	1	1
KAS708151AML	7	1	1
KAS708361OFU	7	1	1

Edges B1 "Intermittent"

SKU	Q	R	SS
104020071	195	0	1
104020267	195	0	9
104020391	195	0	12
104020801	195	5	3
104020893	195	9	6

Edges B4 “Intermittent”

SKU	Q	R	SS
104020233	195	2	1
104020356	195	2	1
104020390	195	264	245
104020893	195	21	17

Appendix 7**:** Q R simulation on Excel

Simulación

SKU	Inv-Inicial	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
TCN4806	Inventario Apertura	25	21	21	17	17	17	15	15	13	7	26	40	39	39	32	29	26	24	24	22
	Venta	4	0	3	0	0	3	0	2	7	0	5	1	0	7	3	3	1	0	3	4
	Reorden	0	0	0	0	0	0	0	0	19	19	0	0	0	0	0	0	0	0	0	0
	Inventario Cierre	21	21	17	17	17	15	15	13	7	7	21	39	39	32	29	26	24	24	22	18

Desv std	3,46
Media	2
Q	19
R	8

Simular