Enhancing Demand Forecasting Accuracy for Retail Equipment

A Quantitative Assessment of Forecasting Methods

Master's thesis in Supply Chain Management

CEREN ÇÖREKÇİ
MARIA GABRIELA MORETTA URDIALES

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF SUPPLY AND OPERATIONS MANAGEMENT
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www.chalmers.se

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Department of Technology Management and Economics
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone +46 (0)31-772 1000

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Abstract

In a globalized world with supply chains becoming more and more complex, the need of being more accurate in predicting future sales becomes essential for companies. In this thesis, the focal company was IKEA Components and the demand forecasting process of the retail equipment was analyzed. The thesis aimed to answer the question of what are the most suitable forecasting methods and parameters to accurately predict the demand for the retail equipment at IKEA Components.
The current method used by IKEA Components was compared with 7 proposed methods and the results showed an accuracy improvement in 87% of the retail equipment stock keeping units (SKU). For the majority of SKUs with smooth demand, the best-performing forecasting method is Moving Average (MA) followed by Double Exponential Smoothing (DES) due to the low fluctuations in demand. For items with erratic demand, the Triple Exponential Smoothing (TES) Additive method stands out for its ability to closely follow the sharp fluctuations in demand. Each suggested method yielding the smallest error for at least one SKU, proved that an *one size fits all* approach is not suitable for the retail equipment at IKEA Components.
As a result from the selection of the best-performing forecasting methods, some insights were found. First, demand patterns were identified and the one that involves the largest portion of SKUs are trend and seasonality occurring simultaneously. Second, correlation in demand behavior between subcategories of SKUs were identified. Furthermore, suggestions on how to further enhance forecast accuracy by applying qualitative assessment were given. Finally, it was theoretically stated that there are positive economic, environmental and social implications of improving the forecasting process.

Keywords: *Demand Forecasting, Forecast Accuracy, Quantitative Forecasting, Retail Equipment, Erratic Demand, Smooth Demand, Lumpy Demand.*

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Ceren & Gabriela, Gothenburg, May 2025

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Ceren Çörekçi, Gothenburg, May 2025

I'd like to take this opportunity to thank my family for being there for me, not only during my thesis, but throughout the entire program, encouraging me and believing in me.

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List of Acronyms

Below is the list of acronyms that have been used throughout this thesis.

ADI	Average Demand Interval
BOM	Bill of Material
CMP	Customer Meeting Point
CPFR	Collaborative Planning Forecasting and Replenishment
CV^2	Coefficient of Variance
DES	Double Exponential Smoothing
ERP	Enterprise Resource Planning
KPI	Key Performance Indicator
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MA	Moving Average
MPS	Master Production Scheduling
MSE	Mean Squared Error
NGO	Non-governmental Organization
S&OP	Sales and Operations Planning
SES	Simple Exponential Smoothing
SKU	Stock Keeping Unit
SS	Seasonal Smoothing
TES	Triple Exponential Smoothing
VMI	Vendor Managed Inventory

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1
Introduction

This first chapter is an introduction to the topic that will be analyzed and discussed in the following chapters. It provides the context of how the problem arose in the focal company and the objectives that are planned to be achieved once the thesis is completed. Additionally, the scope limitations are defined and the research question guiding the study is posed.

1.1 Background

Currently, many multinational companies have globalized supply chains, meaning that different processes, components and products are produced, assembled and distributed to different parts of the world (Sawik, 2018). This used to be a competitive advantage, as manufacturing was done where the cost was lowest and where there were the most resources (Sawik, 2018). Due to current geopolitical and environmental incidents, this strategy is losing its validity, as it is increasingly difficult to cross trade borders (Rasshyvalov et al., 2024). The current trade conflict between the United States and China and the war between Russia and Ukraine negatively impact the flow of resources and merchandise within supply chains (Rasshyvalov et al., 2024). This uncertainty generates alterations in consumption patterns in different regions, creating fluctuations in the sales of strategic products and, in the long term, a potential recession in the affected markets (Khan, 2019).

Inventory management plays a crucial role in mitigating the adverse effects of trade wars on businesses. In order to prevent drastic impacts of disruptions, some companies tend to use inventory to buffer in case of delays in transportation or increased costs (Sodhi & Chopra, 2004). Strategies like the integration of Vendor Managed Inventory (VMI) and supplier diversification, to have better coordination and reduced stockouts, can also mitigate risks associated with trade wars (Mateo & Aghezzaf, 2013). However, there is still a problem on finding the optimal replenishment policy indicating when, how much and from whom they should order (Atan & Snyder, 2011).

Accurate forecasting plays an important role in improving inventory management especially when there is disruption in supply chains since it prevents overstocking, under-stocking and stock-out of inventory (Singh, et al., 2024). For companies, having accurate demand forecast could increase profit by a significant margin reducing the costs associated with excess inventory and emergency procurement. (Konda, et al., 2023, Martin & Frei, 2003).

IKEA Components

IKEA is a company that started as a small mail-order company in rural Sweden and it has grown into a global home furnishing brand (IKEA, 2024). IKEA is widely recognised as a leader in international furniture retailing (IKEA, 2024). Guided by its vision to "create a better everyday life for the many people," IKEA employs a clear strategy of cost optimization without compromising quality (IKEA, 2024). IKEA organization operates 480 stores in 63 markets and generates annual sales of EUR 45.1 billion (IKEA, 2024).

The company is structured into two main groups: IKEA franchisees, responsible for operating stores in their 63 markets, and the Inter IKEA Group, which oversees the sourcing, development, and distribution of IKEA's product range. Within Inter IKEA Group, IKEA Components is responsible for supplying the components to assemble the final products.

According to the Supply Chain Manager, three years ago, IKEA Components got assigned the responsibility of managing the inventory of the equipment required to build and maintain the customer meeting points (CMP) that include pick-up points and stores. This task is crucial for IKEA Components, since the franchisees are committed to deliver a consistent customer experience across all its stores worldwide, ensuring that customers experience the same brand concept and identity regardless of their location. These equipment is visible in the CMP and required for them to operate, however, cannot be purchased by the end customers. These items are referred to as "retail equipment" and include a diverse range of products such as staff uniforms, promotional banners, and price tags.

According to the Demand Planner, one of the challenges that IKEA Components faces when managing the retail equipment inventory is obtaining comprehensive, accurate and on-time input from their internal customers. When the IKEA franchisees create projects related to remodeling or constructing new CMP, the demand patterns of the retail equipment are impacted. IKEA franchisees do provide some forecast input, however, it is often incomplete or not shared early enough for IKEA Components to react to this demand peak. This mismatch occurs due to the long-term horizon of the replenishment planning of IKEA Components. As a result, Demand Planners generate the forecasts themselves basing their inputs mainly in historical sales.

The second challenge that IKEA Components is facing is the use of a single forecasting method used to predict the demand of the entire product range as it is the only method available in their current ERP system. This is considered a challenge because each stock keeping unit (SKU) behaves differently, and trying to forecast them with a single method is unlikely to accurately predict future demand. As a consequence, the Supply Chain Manager explained that in the past there has been inefficiencies in the forecasting process leading to unhealthy inventory levels.

Overall, there are two undesirable extremes when it comes to inventory management: on one hand, excess inventory increases storage costs and generates waste; on the other, stock-outs disrupt store operations and negatively impact the customer experience. Both of these extremes undermine IKEA Components' sustainable goals.

IKEA Components is currently transitioning to a new Enterprise Resource Planning (ERP) system that offers a wide range of demand forecasting methods. Each method within the ERP portfolio is designed to respond to a specific consumption pattern. Therefore, an analysis of individual SKU demand behavior is required to identify the method that most accurately predict the franchisee's demand.

1.2 Aim

The aim of this thesis is to increase the accuracy of the retail equipment demand forecast by understanding the demand patterns, assessing different forecasting methods with their parameters. By selecting the best-performing method that accurately predicts future demand, IKEA Components ensures smooth and continuous store operations.

1.3 Limitations

Due to the time and resource constraints inherent in a master's thesis study, the scope of the forecast analysis is delimited. The assessment of the forecasting methods is limited to the most critical and well-known in the literature. Additionally, an integration of judgmental assessment is not included in the analysis; however, suggestions on how to implement it in the forecasting processes is given in the Results & Discussion Chapter. Finally, the pricing of the retail equipment as a variable in the analysis is excluded due to IKEA's privacy policy, which does not allow this information to be disclosed.

1.4 Research Question

To achieve the aim of this study, which is to improve the accuracy of demand forecasting in retail equipment, the following research question has been formulated.

RQ. *What are the most suitable forecasting methods and parameters to accurately predict the demand for different retail equipment SKUs within IKEA Components?*

The research question is used as a guideline for the methodology, analysis, results, and discussion.

2

Literature Review

Any research study, inductive or deductive, that is undertaken for academic purposes, will always require a review of relevant literature (Bryman & Bell, 2015). A clear idea of the theoretical context of a piece of research helps clarify its purpose and outcomes and makes clear which situations the findings do or do not hold (Bryman & Bell, 2015). This chapter aims to provide a background on demand forecasting and lay the foundation for widely recognized forecasting methodologies. It also takes an in-depth look at the consequences of poor demand forecasting for social and environmental sustainability.

2.1 Demand Forecasting

Measured, expected, and somewhat affectable (by internal forces like marketing or pricing) estimation of future demand is called a forecast (Jonsson & Mattsson, 2009). Forecasting is a fundamental part of the short, medium, and long-term decision-making and planning of critical processes such as Sales and Operations Planning (S&OP), Master Production Scheduling (MPS), and so on (Jonsson & Mattsson, 2009).

The inputs that forecasting provides are interpreted on different levels for the different processes in the planning hierarchy. While it is usually aggregated in product groups for S&OP, it would be in SKU level for MPS, and raw material level for sourcing processes (Jonsson & Mattsson, 2009). Forecasting should be based on the expected demand in the market by considering any measurable qualitative and quantitative input but not how much the company aims to sell (Jonsson & Mattsson, 2009). Having errors in the forecast is inevitable by its nature due to deficient modeling assumptions, flawed data, inadequate combinations of quantitative and qualitative aspects, unrealistic judgment, lack of accountability, and so on (Jonsson & Mattsson, 2009).

High demand uncertainty is another factor that makes accurate forecasting more challenging in today's dynamic marketing conditions. Collaborative Planning Forecasting and Replenishment (CPFR) is a response to the need for resource and effort collaboration of different functions and organizations (Jonsson & Mattsson, 2009). CPFR was initiated in 1995 to increase transparency among organizations to reduce the impact of uncertainties and to improve the connection between demand and replenishment (Da Silva et al., 2024). CPFR was built on five main principles (Jonsson & Mattsson, 2009):

1. The relationship should be based on mutual trust and joint goals and activities.
2. Joint forecast is used as a basis for the planning processes of both customer and supplier sides.
3. Core competencies of each agent should be performed to benefit the collaboration irrespective of the resource owner.
4. To benefit the end consumer, common Key Performance Indicators (KPIs) should be in place.
5. Benefits and risks that may arise should be shared among the actors based on their roles.

A well-implemented CPFR can overcome the inefficiencies that arise due to not aligning the individual planning efforts of the companies (Jonsson & Mattsson, 2009).

Time Series and Demand Patterns

Time series constitutes a collection of realized demand represented in equal intervals, which allows observing patterns like random variations, trends, and seasonal variation, which provides insights for forecasting (Jonsson & Mattsson, 2009). A time series is said to have a trend if periodic an increase and decrease is observed over the demand data, whereas time series with seasonal variation show increase or decrease over the same period of the year (Jonsson & Mattsson, 2009).

A more in-depth analysis of time series data allows for a systematic classification of demand patterns through the application of variance partitioning (Williams, 1984). This method integrates both the Squared Coefficient of Variation (CV^2) of demand sizes which is calculated as the division of the standard deviation by the mean of historical demand, and the Average Demand Interval (ADI), calculated by dividing the number of periods by the number of non-zero demands (Williams, 1984). In this way, four demand categories emerge, as shown in Table 2.1 where smooth demand refers to consistent, predictable, and high-frequency demand, erratic demand has high variability but frequent demand, intermittent demand is highly infrequent but can be consistent in size and lumpy demand is highly variable, completely unpredictable and sporadic and the most difficult pattern to forecast (Syntetos & Boylan, 2005).

Table 2.1: Demand Type Classification

Category	ADI	CV^2	**Description**
Smooth	< 1.32	< 0.49	Regular and predictable demand.
Erratic	< 1.32	≥ 0.49	Irregular in volume, but occurs frequently.
Intermittent	≥ 1.32	< 0.49	Low volume, appears infrequently, low variability.
Lumpy	≥ 1.32	≥ 0.49	Unpredictable and sporadic demand

Demand forecasting methods that use time series could only exploit the patterns in the historical demand data. On the other hand, regression models could benefit the historical behavior of other independent series by identifying the causal relationship between the dependent variable (demand) and the independent variables (other demand determinants) (Nahmias & Olsen, 2015).

Forecasting Horizon and Aggregation Level

Obtaining, storing, and using relevant and appropriate data sets is a prerequisite for a successful forecast; however, it is not always possible due to the difficulties in representing the real demand data for ERPs (Jonsson & Mattsson, 2009). Stock-outs, capacity limitations, and delivery schedule deviations can shift "perceived demand" amounts. Therefore, sales or order information does not always reflect the "actual demand," which makes the reliability of the data for a strong forecast questionable (Jonsson & Mattsson, 2009).

It is possible to examine the classification of forecasting horizon in short, intermediate, and long terms (Nahmias & Olsen, 2015). Short-term forecasts are useful for operational decisions and are usually expressed in days/weeks; intermediate-term forecasts are useful for midterm decisions like resource requirements and expressed in weeks/months; finally, long-term forecasts may be used for more strategic decision-making such as capacity expansion, usually expressed in months/years (Nahmias & Olsen, 2015). Forecast horizon decision is critical as it should be appropriate for the planning reasons and needs but also will impact the forecast precision (Jonsson & Mattsson, 2009).

The aggregation level of the forecast can help improve precision and could provide insights for strategic planning; usually, forecasting the parent items tends to have less variation historically and could then be allocated to child units or even to the bill of material (BOM) level (Jonsson & Mattsson, 2009).

2.2 Forecasting Methods

Forecasting methods can be classified as qualitative and quantitative, qualitative methods are usually based on expert judgment and are subjective to the person, whereas quantitative methods use calculations based on reasonable logic and objective judgment (Jonsson & Mattsson, 2009). Casual methods observe the relationship between the demand and explanatory variables and tend to be computationally more complex, while time series methods use only the historical data of the unit to be forecasted (Jonsson & Mattsson, 2009). A forecasting method should be resisting to random fluctuations in demand while being able to catch systematic changes (Jonsson & Mattsson, 2009).

2.2.1 Qualitative Forecasting

Qualitative forecasting, also known as subjective, includes very few and non-complex calculations, if not none, useful when the horizon is long and the forecast is expected to be influenced by the firm's internal activities (Jonsson & Mattsson, 2009).

Sales Force Composites Approach is using the insights provided by the sales department's employees as they have direct contact with the customers; they might tend to underestimate the amounts as it will impact sales personnel's bonuses in case they exceed the expectations (Nahmias & Olsen, 2015). These forecasts can be several numbers with scenario-based probabilities; individual results from salespeople then can be aggregated by sales management and grouped at the relevant product family level (Nahmias & Olsen, 2015).

Customer Surveys are a base to understand upcoming trends in the industries; however, they should be designed in a way to eliminate bias and reflect the intended customer base (Nahmias & Olsen, 2015).

Jury of Executive Opinion refers to joining the executive opinion from several strategic departments and could be useful in case of a new product launch and no historical demand data available (Nahmias & Olsen, 2015).

The Delphi Method also combines expert opinions gathered through individual surveys aiming to remove the possibility of the dominant personalities overshadowing the others in a group dynamic (Nahmias & Olsen, 2015). Experts can later view the collective feedback on their individual opinions, and this is iterated until a consensus has been reached (Nahmias & Olsen, 2015). This methodology creates a space for expressing uninfluenced opinions; however, it creates dependence on well-designed questionnaires and assumptions that the consensus will be achieved (Nahmias & Olsen, 2015).

2.2.2 Quantitative Forecasting

Quantitative forecasting, also known as objective, includes methods that observe the data from an analytical perspective (Nahmias & Olsen, 2015).

Methods for Stationary Demand

Stationary demand is a time series that can be represented as $D(t) = \mu + \varepsilon(t)$ where μ is a representation of the mean of the series and $\varepsilon(t)$ is a random error with mean zero and variance σ^2 (Nahmias & Olsen, 2015). See Fig. 2.1.

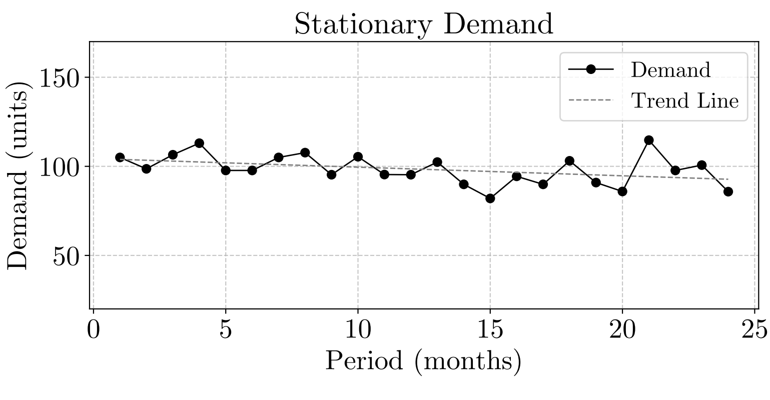

Figure 2.1: Stationary time series with random variation.

2.2.2.1 Moving Average

Moving Average (MA) is a representation of the average demand of certain past periods where the number of period decision is impacted by the duration of the period, variation, and other characteristics unique to specific demand (Jonsson & Mattsson, 2009). The longer the period used, the less sensitive the forecast is to random fluctuations; however, longer periods tend to miss trend behavior (Jonsson & Mattsson, 2009). To calculate the forecast for the period $t + 1$ see the following formula:

$$F_{t+1} = \frac{(D_t + D_{t-1} + ... + D_{t-n+1})}{n} \tag{2.1}$$

Where,

F_{t+1} = demand estimate for time $t + 1$

D_t = realized demand during period t

n = number of periods

One drawback of the MA method could be that it gives the same weight to all past periods used in the forecast, which would result in lagging if the series is not stationary (Jonsson & Mattsson, 2009). The choice of n is a trade-off between the reactivity and the stability of the forecast (Jonsson & Mattsson, 2009). A smaller n makes the forecast more reactive to the changing patterns in more current periods, whereas a larger n would yield more stable forecasts (Jonsson & Mattsson, 2009). As the MA Method assumes a stationary demand, any forecast of F_{t+n} will be the same as the one for F_{t+1}, although accuracy is expected to decrease as the horizon increases (Nahmias & Olsen, 2015).

2.2.2.2 Simple Exponential Smoothing

Compared to MA, Simple Exponential Smoothing (SES) allows giving a geometric weight to past observations whose summation adds up to 1 and requires fewer data points, namely the last observation and the latest forecast (Jonsson & Mattsson, 2009). To calculate the forecast for the period $t + 1$ see the following formula:

$$F_{t+1} = \alpha D_t + (1 - \alpha)F_t \tag{2.2}$$

Where,

F_{t+1} = demand estimate for time $t + 1$

D_t= realized demand during period t

α = smoothing factor for level; where 0< α <1

To relate the smoothing factor to the period n in the MA, $\alpha \approx \frac{2}{n+1}$ approximation could be referred to (Jonsson & Mattsson, 2009). A large α will increase the impact of the latest observed demand on the forecast, which will increase the reactivity in case of a sudden change in demand; however, it will reduce the stability of the forecast among the periods, and a smaller α will cause the opposite results (Nahmias & Olsen, 2015). Because an initial forecast is needed for the start of SES, the latest demand could be used; however, this would increase the impact of the last period even more; therefore, forecasting F_t with different α values and taking the average can offer a smoother starting point (Nahmias & Olsen, 2015).The forecast for the period $t + \tau$, is the same as that for period t+1 because of the stationary demand assumption when doing multiple-step ahead forecasting using SES therefore, these methods are not necessarily ideal for trend or seasonality (Nahmias & Olsen, 2015). Because both SES and MA lag behind in the case of a trend in the series, different methods are needed to account for it.

2.2.2.3 Croston

As previously mentioned, a demand is called to be intermittent if there exist random gaps of time periods with zero demand, making it challenging to achieve an accurate forecast (Xu et al., 2012). The source of the challenge is the dual-objective problem: estimating the size of the gap with no demand (inter-arrival time), and the quantity of the demand (Xu et al., 2012). Croston's Method provides a solution to this challenge, by updating the forecast estimate only when a positive demand occurs (Xu et al., 2012). Croston's method uses SES where the smoothing is done both on the interval and demand size series (Hyndman & Shenstone, 2005).

Hyndman & Shenstone (2005), provides the equations to execute forecast with Croston's method as follows;

$$\hat{Y}_{n+h} = \frac{Z_\ell}{P_\ell} \tag{2.3}$$

$$Z_j = (1-\alpha)Z_{t-1} + \alpha Y_j^* \tag{2.4}$$

$$P_j = (1-\alpha)P_{j-1} + \alpha Q_j \tag{2.5}$$

Where:

j_t = number of periods with nonzero demand during interval $[0, t]$

l = last period of demand

$\hat{Y}_{n+h}$ = demand estimate for time $n + h$

Z_ℓ = latest estimate for demand size

P_ℓ = latest estimate for inter-arrival time

Z_j = estimate for demand size

Y_j^* = most recent non-zero demand size

P_j = estimate for inter-arrival time

Q_j = most recent inter-arrival time

α = smoothing factor ; where $0< \alpha <1$

Methods for Demand with Trend

Time series that demonstrate an increase or decrease by time are defined as demand with trend. See Fig. 2.2.

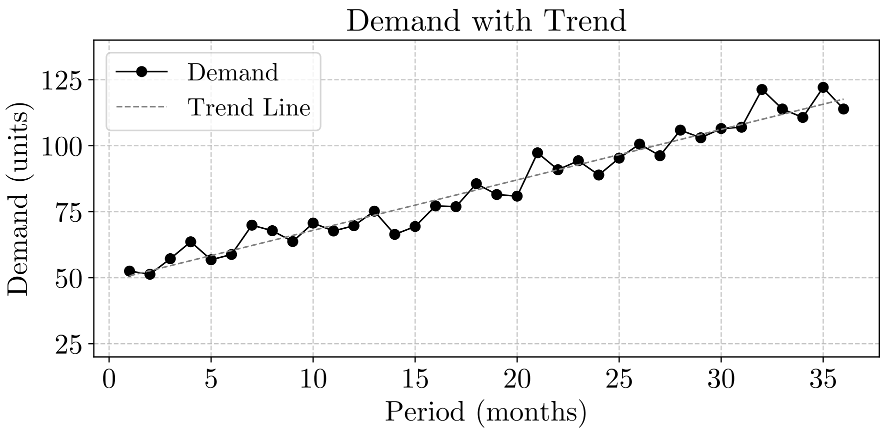

Figure 2.2: Time series with increasing trend

2.2.2.4 Double Exponential Smoothing

Double Exponential Smoothing (DES) is a common forecasting method that may be useful for time series with only linear trend observed and has two smoothing constants α for level and β for trend (Nahmias & Olsen, 2015).

$$S_t = \alpha D_t + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{2.6}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \tag{2.7}$$

Where,

S_t = level estimate at time t

G_t= slope value at time t

α = smoothing factor for level; where 0< α <1

β = smoothing factor for trend; where 0< β <1

Equation (2.6) is a weighted average of the latest demand with the forecast of the previous period's slope, similar to the SES, whereas Equation (2.7) updates the slope estimation using a new intercept estimate along with the forecast of the previous period's slope (Nahmias & Olsen, 2015). Choice of β impacts the change rate of the slope estimate, smaller β is more suitable for a slowly changing trend over time (Hyndman & Athanasopoulos, 2018). Here it is more common to desire stability for slope estimation, therefore more likely to have $\beta \leq \alpha$ (Nahmias & Olsen, 2015). Multi-step ahead forecasting can be done with the following formula:

$$F_{t,\tau} = S_t + \tau G_t \tag{2.8}$$

Where,

$F_{t,\tau}$ = demand estimate for τ periods ahead at time t

Methods for Demand with Seasonality

A time series that shows a similar behavior at a certain time on the time horizon is called demand with seasonality. See Fig. 2.3.

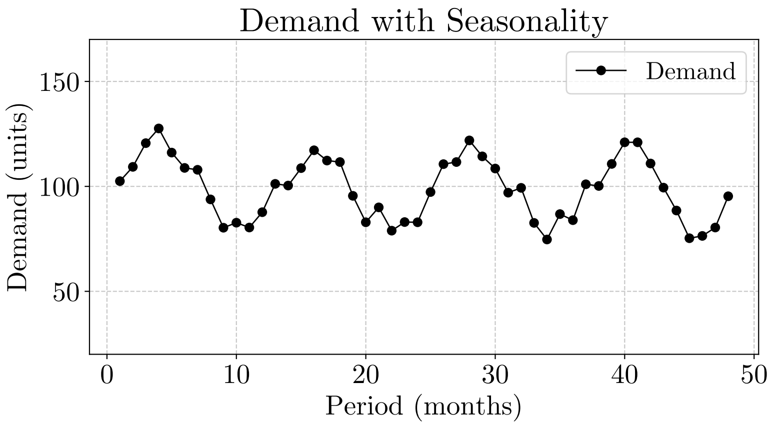

Figure 2.3: Time series with seasonality.

Hyndman and Athanasopoulos (2018) explain how Holt-Winter's Seasonal Method, also known as Triple Exponential Smoothing (TES), introduces two new parameters γ for seasonal smoothing, and m to denote the frequency of seasonality. The authors classify the seasonal component into two types: multiplicative and additive seasonality. The multiplicative method performs better when the seasonal component differs proportionally to the series level, whereas the additive representation provides a better estimate when the seasonality component is rather constant over time (Hyndman & Athanasopoulos, 2018).

2.2.2.5 Triple Exponential Smoothing (Multiplicative)

This method is suitable for demand data that shows a seasonal pattern where seasonal components have a proportional relation to the level. In the case of a stable level of demand, additive, and multiplicative TES Methods yield similar results; however, in the case of a seasonal pattern change in proportion to level changes, the multiplicative model is more suitable (Gardner, 1985). Smoothing equations for TES Multiplicative Method adapted from Gardner, (2006) are:

$$F_t = (S_{t-1} + G_{t-1})C_{t-m} \tag{2.9}$$

$$S_t = \alpha(D_t/C_{t-m}) + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{2.10}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \tag{2.11}$$

$$C_t = \gamma(D_t/S_t) + (1-\gamma)C_{t-m} \tag{2.12}$$

Where,

F_t = demand estimate for time t

S_t = level estimate at time t

G_t= estimate of the trend at time t

C_t= seasonality estimate at time t

m = frequency of seasonality

α = smoothing factor for level; where 0< α <1

β = smoothing factor for trend; where 0< β <1

γ = smoothing factor for seasonality; where 0< γ <1

Equation (2.10) is the weighted average of the demand at time t adjusted by the multiplicative seasonality index of the last year of this period and the non-seasonal forecast for time t. Equation (2.11) is identical to Equation (2.7) in DES. Equation (2.12) is a weighted average of demand at time t adjusted by the current multiplicative seasonal index and the seasonal factor of the same period of the previous period. The length of seasonality frequency is defined by m, assuming a yearly seasonality m value should be 12 (Hyndman & Athanasopoulos, 2018).

2.2.2.6 Seasonal Smoothing (Multiplicative)

Gardner (2006) explains Holt-Winter's exponential smoothing in several different versions. Seasonal Smoothing (SS) Multiplicative is a modification of the TES where the trend component is excluded. Below are equations derived from Gardner (2006) to explain SS without trend. Application of the SS Method with no trend is observed in utility demand like natural gas (Gardner, 2006). Smoothing equations for SS Multiplicative Method adapted from (Gardner, 2006) are:

$$F_t = S_{t-1}C_{t-m} \tag{2.13}$$

$$S_t = \alpha(D_t/C_{t-m}) + (1-\alpha)(S_{t-1}) \tag{2.14}$$

$$C_t = \gamma(D_t/S_t) + (1-\gamma)C_{t-m} \tag{2.15}$$

Where,

F_t = demand estimate for time t

S_t = level estimate at time t

C_t= seasonality estimate at time t

m = frequency of seasonality

α = smoothing factor for level; where 0< α <1

γ = smoothing factor for seasonality; where 0< γ <1

Equation 2.13 suggests a forecast as the product of the previous level value and last year's seasonality index of the current period. Equation (2.14) is the weighted average of the demand at time t adjusted by the multiplicative seasonality index of the last year of this period and the level for time $t-1$. Equation (2.15) is a weighted average demand at time t adjusted by the current level and seasonality index of the last year of this period.

2.2.2.7 Triple Exponential Smoothing (Additive)

This method is suitable for demand data which shows a seasonal pattern with a roughly constant seasonal component (Hyndman & Athanasopoulos, 2018). Smoothing equations for the TES Additive Method adapted from (Gardner, 2006) are:

$$F_t = S_{t-1} + G_{t-1} + C_{t-m} \tag{2.16}$$

$$S_t = \alpha(D_t + C_{t-m}) + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{2.17}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1} \tag{2.18}$$

$$C_t = \gamma(D_t - S_t) + (1-\gamma)C_{t-m} \tag{2.19}$$

Where,

F_t = demand estimate for time t

S_t = level estimate at time t

G_t= estimate of the trend at time t

C_t= seasonality estimate at time t

m = frequency of seasonality

α = smoothing factor for level; where 0< α <1

β = smoothing factor for trend; where 0< β <1

γ = smoothing factor for seasonality; where 0< γ <1

Equation (2.17) is the weighted average of the demand at time t adjusted by seasonality and the non-seasonal forecast for time t. Equation (2.18) is identical to (2.7) in DES. Equation (2.19) is a weighted average with the smoothing factor γ of the current seasonal factor, and the seasonal factor of the same period of the previous period.

2.2.2.8 Seasonal Smoothing (Additive)

Seasonal Smoothing (SS) Additive without trend is again a modification of Holt-Winters TES explained in Gardner (2006). Different from the method in 2.2.2.5, this version assumes an additive seasonality component. Smoothing equations for the SS Additive Method adapted from (Gardner, 2006) are:

$$F_t = S_{t-1} + C_{t-m} \tag{2.20}$$

$$S_t = \alpha(D_t - C_{t-m}) + (1-\alpha)(S_{t-1}) \tag{2.21}$$

$$C_t = \gamma(D_t - S_t) + (1-\gamma)C_{t-m} \tag{2.22}$$

Where,

F_t = demand estimate for time t

S_t = level estimate at time t

C_t= seasonality estimate at time t

m = frequency of seasonality

α = smoothing factor for level; where 0< α <1

γ = smoothing factor for seasonality; where 0< γ <1

To summarize the forecasting methods, Table 2.2 shows a comparison of the applicability of each one of them and its limitations.

Table 2.2: Summary of Forecasting Methods with their Applicability and Limitations

Forecasting Method	**Type**	**Best Use Case**	**Limitations**
Sales Force Composite	Qualitative	When sales personnel have direct insights into customer demand.	May be distorted by the personal motives of salespeople.
Customer Surveys	Qualitative	Provides a clear understanding of customer needs.	Risk of bias due to survey design.
Jury of Executive Opinion	Qualitative	Useful to make strategic decisions (e.g. new product launched).	Depends on the accuracy of executive judgments.
Delphi Method	Qualitative	To remove dominant personalities' influence in expert opinions; best for strategic planning.	Relies on well-structured questionnaires.
MA	Quantitative	Suggested method for stationary demand.	It might lag behind trends.
SES	Quantitative	For stationary demand with some responsiveness to recent changes; requires smoothing factor tuning.	High dependency on the smoothing factor α.
Croston	Quantitative	Suggested for intermittent demand.	Doesn't update forecasts when zero demand.
DES	Quantitative	Useful for time series with a linear trend.	Assumes a linear trend, does not account for seasonality.
TES - Multiplicative	Quantitative	Suitable for data with seasonal patterns proportional to the level.	The multiplicative seasonality component makes the forecast sensitive to level changes.
SS - Multiplicative	Quantitative	Suitable for demand data with seasonality but no trend.	Does not consider trends and poor perform for non-stationary demand.
TES - Additive	Quantitative	Suitable for demand data with seasonal patterns with constant seasonal components.	Not suitable for demand with trend that change over time.
SS - Additive	Quantitative	Used for seasonal with an additive seasonality component.	Does not account for trends, poor performance for non-stationary demand.

2.3 Performance Measurement

To estimate the performance of forecasting methods, numerous studies have adopted various accuracy measures as evaluation criteria, proposing different metrics for both regression and classification problems while extensively discussing their relevance and applicability (Mehdiyev et al., 2016). According to Nahmias and Olsen (2015), forecast error is defined as the difference between the predicted value and the actual demand for a given period, and it plays a role in evaluating the effectiveness of a forecasting method. The forecasting error in time t is:

$$e_t = F_t - D_t \tag{2.23}$$

Nahmias and Olsen (2015) suggest two common measures of forecast accuracy, and these are Mean Absolute Deviation (MAD) and Mean Squared Error (MSE), which are formally defined as follows:

$$MAD = \frac{\sum_{i=1}^{n} |e_i|}{n} \tag{2.24}$$

$$MSE = \frac{\sum_{i=1}^{n} e_i^2}{n} \tag{2.25}$$

Where,

e_i = forecast error in period i

n = number of periods

Nahmias and Olsen (2015) suggest another measurement that is used as well, the Mean Absolute Percentage Error (MAPE), which does not depend on the magnitude of the values of demand, and the formula is:

$$MAPE = \frac{\sum_{i=1}^{n} \frac{e_i}{D_i}}{n} 100 \tag{2.26}$$

Where,

e_i = forecast error in period i

D_i = demand in period i

n = number of periods

A desirable property of forecasts is that they must be unbiased in mathematical terms that $E(e_i) = 0$ (Nahmias and Olsen, 2015). A simple way to track if this is happening is to graph the values of the forecasting error over time, and they should fluctuate randomly below and above zero (Nahmias & Olsen, 2015).

To sum up, Table 2.3 highlights the applicability, advantages and disadvantages of each accuracy measurement.

Table 2.3: Summary of Forecasting Accuracy Measures

Accuracy Measure	Applicability	Advantages	Disadvantages
MAPE	Useful when the scale of data is not fixed.	Easy to interpret as a percentage. Facilitates comparison across different datasets since it is widely used in the industry.	Unable to calculate when demand is zero. Asymmetrical, penalizing positive and negative errors differently.
MAD	Useful when comparing forecast accuracy in the same dataset.	Easy to calculate.	Not suitable for comparing across datasets with different scales.
MSE	Suitable when scale based penalty is required. It is commonly used in statistical modeling and machine learning.	Penalizes larger errors more due to squaring, which can be useful in certain contexts.	Not suitable for comparisons across different datasets.

2.4 Forecasting and Sustainability

Raworth's (2017) Doughnut Theory provides a framework for balancing human needs with planetary limits. This model integrates a social foundation, which includes fundamental human necessities such as health, food, water, education, and income, with an ecological ceiling that safeguards the natural regeneration of ecosystems (Raworth, 2017). Maintaining this balance helps ensure human well-being while also preventing environmental issues like air pollution, climate change, and loss of biodiversity (Raworth, 2017)

It is challenging to balance production and demand, and this has a high impact on society and the environment (Shimell, 1991). As a result of this frequent imbalance between production and demand, waste of overproduced products is created (Darlington & Rahimifard, 2009). Darlington and Rahimifard (2009) suggest two main reasons for the waste, obsolescence and deformation, mainly caused by long periods of stacking in the warehouse. (Darlington & Rahimifard, 2009). At the same time, products with low monetary value and high storage costs, since it negatively impacts profit margins, are usually disposed (Pourhejazy, 2020). Businesses also decide to get rid of less important goods when warehouse capacity is limited and demand for new or high-priority products spikes (Pourhejazy, 2020).

As these overproduced products start decomposing, they not only pollute the environment but also involve a waste of the resources spent to produce them (Cockborne et al., 1999; Domínguez & Gómez-Brandón, 2012; Uniyal et al., 2017). It should not be disregarded that the production, distribution, and storage of these products are also sources of greenhouse gas emissions (Ai, 2000; Donohoe, 2003; Taghikhah et al., 2019).

Environmental sustainability depends on waste management techniques like recycling and disposal, but social sustainability can be jeopardized by its improper execution (Clapp, 2001). Clapp (2001) highlights hows the improper waste management practices of developing companies export their waste to countries with leaks in their laws. Local communities in those underdeveloped countries who import the waste, deal with environmental damage and health problems caused by this imbalance. Concerns about the environmental justice emerge because of the uncontrolled trash disposal practices of the wealthy countries. Chunsuttiwat and Coxhead (2024) prove that the trade patterns in plastic garbage are changing in favor of wealthy countries.

Martuzzi et al. (2010)'s research shows evidence proving that waste disposal sites, such as landfills, incinerators, and hazardous waste facilities, are often found in neighborhoods with larger ethnic minority populations or in economically disadvantaged areas. Whether this trend is lawful or not, it raises questions regarding environmental justice and trash management equity (Martuzzi et al., 2010).

As a preventive measure to reduce unnecessary excess inventory, it is essential to return to upstream inventory management processes, that is, to evaluate demand forecasts and their replenishment policies (Adhikari et al., 2018; Suki, 2015). At the same time, it is important to understand the industry specifics and the available technological capabilities of forecasting algorithms for an optimal inventory management (Bayus et al., 1989; Verma et al., 2021).

Overall, accurate demand forecasting minimizes the damage caused to the environment by overproduction and excess inventory. Recycling and disposal techniques help manage waste, but their proper use is necessary to ensure social, economic, and environmental sustainability.

3 Methodology

This chapter describes the methodology used to conduct the study. It begins with a description of the research design, the data collection process, the selection of the forecasting methods to be evaluated, and the selection of the evaluation metric. It then describes, the *as is* situation and, finally, explains how the forecasting methods are evaluated.

3.1 Research Design

The research design proposed for this thesis is a case study. This type of investigation is ideal when a deeper understanding of either a specific process or event is required (Säfsten & Gustavsson, 2020). This thesis aims to analyze one of the processes within the replenishment planning of retail equipment: the demand forecasting process. The most significant aspect of case studies is that they allow researchers to study the process or phenomenon in its natural environment, discovering many aspects of its current conditions (Säfsten & Gustavsson, 2020).

The object of this study is to identify the most suitable forecasting algorithms and parameters for IKEA Components' retail equipment. Therefore, it is necessary to adopt a quantitative approach that measures the accuracy of current demand forecasting and objectively compares it with the forecast accuracy of the proposed methods.

Figure 3.1 contains the methodology flowchart that illustrates the step-by-step to be followed in the analysis and each step is explained in detail in the following sections.

3.2 Data Collection

This thesis contains primary and complementary data depending on the function they fulfill within the analysis. The primary data is purely quantitative and is based on the historical demand of 2244 SKUs from January 2021 until December 2024. It was decided to select a historical demand greater than one year to detect seasonality patterns. However, dates before 2021 were excluded due to the global sales impact of the 2020 pandemic.

The quantitative data is received in a disaggregated form through purchase orders made by customers, which in this case are IKEA franchisees. However, for the purpose of this thesis, the data will be analyzed in a disaggregated manner by items but

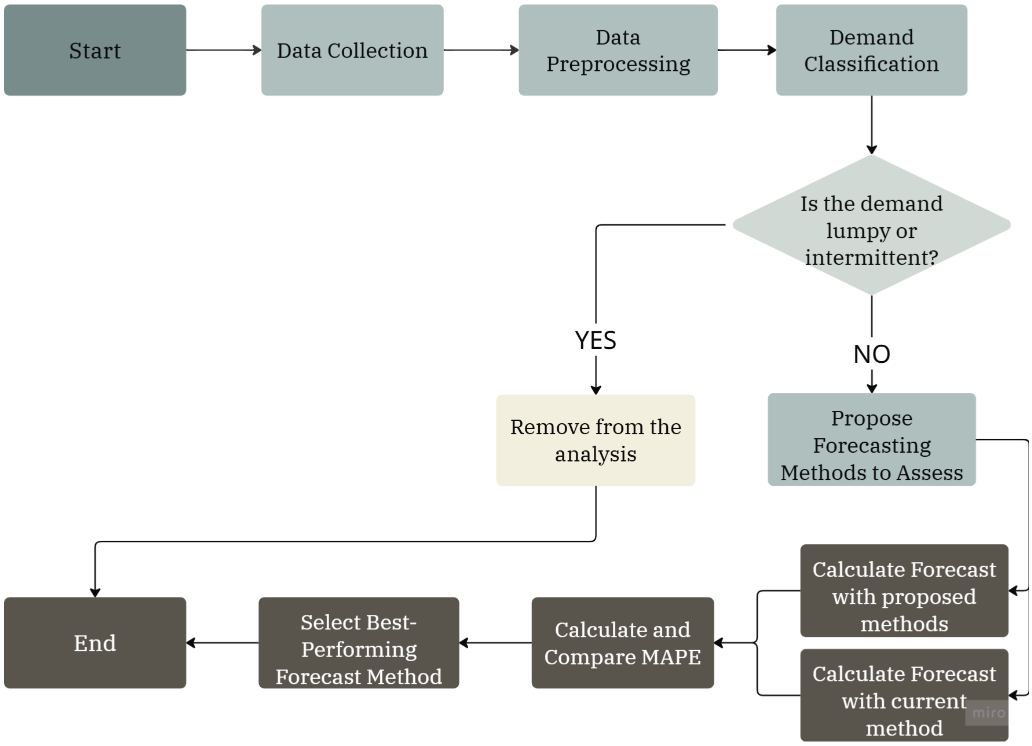

Figure 3.1: Methodology Flowchart for Forecasting Method Selection.

aggregated by months, as this is the level of granularity currently used in forecast generation. This level of granularity is influenced by the need for desirable precision, as a more aggregated forecast tend to have less variation and higher accuracy (Jonsson & Mattsson, 2009). For retail equipment, disaggregation to BOM level was not relevant, as IKEA Components does not manufacture its range themselves; they purchase the complete product. Finally, the source of the data comes from IKEA Components' centralized online channel, which consolidates and processes all orders placed by the different franchisees globally.

Within the complementary information, it was provided a master data file containing detailed information on the individual SKUs including its description, its ABC classification and its category. Each SKU is classified into three hierarchical category levels. For example, the SKU "shirt long sleeve shape V yellow" falls under the shirts subcategory, which is part of the broader tops category within the main co-worker clothing category. These categories are essential to later analyze demand patterns at different levels of granularity.

The second set of complementary information is qualitative and was collected through interviews with various stakeholders from IKEA Components. These interviews provided insights into how the replenishment planning process of retail equipment works and the purpose of demand forecasting within it.

3.2.1 Interviews

Ten formal interviews with different stakeholders within IKEA Components provided a foundation for gaining a clear picture of the background of the problem and a complete understanding of the current demand forecasting process. In addition, external factors that might affect forecast accuracy and their implications were also discussed in the interviews. Please refer to Table 3.1 for the interviews details. In addition to these formal and introductory interviews, on-demand meetings were arranged with the stakeholders to provide further clarifications during the study.

Table 3.1: Overview of Interviews Including Interviewees, Topic of Discussion and more Details

Interviewee	**Topic**	**Date**	**Type**
Supply Chain Manager	Company overview, Business Unit background, problem definition, scope delimitation and confidentiality policies.	February 3rd, 2025	In-person
Demand Planner	Current demand forecasting process (including method, parameters, time horizon, and judgmental assessment).	February 3rd, 2025	In-person
Business Process Leader	Business & Organization background.	February 3rd, 2025	Remote
Need Planners	Demand forecast criticality for need planning processes.	February 4th, 2025	In-person
Market Manager	Marketing insights related to market expansion (new CMP) and renovation process of existing stores.	February 4th, 2025	In-person
Category Manager	Demand forecast implications in purchasing & supplier management.	February 4th, 2025	In-person
Demand Planner	Capabilities of the New ERP forecasting process.	February 5th, 2025	In-person
Demand Planner	Calculation of current demand forecast accuracy.	February 5th, 2025	In-person
Store Manager	Guided visit to Älmhult's IKEA store to grasp customer needs firsthand.	February 5th, 2025	In-person

3.2.2 Observations

Observational research can be classified depending on its structure and the level of participation (Bryman & Bell, 2015). Unstructured observations are more flexible and exploratory, and structured observations follow to a predetermined framework (Bryman & Bell, 2015). Similarly, when the researcher actively participates in the environment it is participant observation while when they do not intervene it is a non-participant observation.

To gain a deeper understanding of the context of the problem, the forecasting process flow including the calculation of the demand forecast and its accuracy measurement were simulated for the researchers to observe. To ensure that it was as realistic as possible, this was done in an unstructured manner and without the researchers direct involvement. During the observation, questions that arose at the time were asked, which shed light on the process.

3.2.3 Ethical Compliance and Data Confidentiality

It is important to note that all necessary permissions were obtained to access and use the data described above, ensuring ethical compliance with IKEA Components' policies. In the same manner, IKEA Components's internal files are confidential and cannot be disclosed in this study. All analyses and findings presented are derived from anonymized and aggregated data to maintain data integrity and confidentiality.

3.3 Data Preprocessing & Cleaning

Preprocessing is the practice of cleaning, altering, and reorganizing raw data for an effective and unbiased data analysis (El Morr et al., 2022). Data preparation is the first stage to ensure that the raw data are refined, standardized, and free of inconsistencies (El Morr et al., 2022). This section describes the steps to transform data into a suitable format for the next steps. By applying these preprocessing steps, the dataset becomes more reliable, improving the accuracy of the forecasting models and subsequent analyses.

1. Scoped-out SKUs: To clearly identify demand patterns such as seasonality, it was necessary to have more than 24 periods of demand, therefore those SKUs that did not match this requirement were removed from the analysis. Similarly, items that had no historical demand in the last 12 periods were eliminated since it was not possible to have reliable results with outdated data. As a result, 326 SKUs are eliminated from the scope of this study.
2. Data Transformation: To avoid errors when calculating the forecast accuracy, some adjustments to historical demand were necessary. First, periods where its demand was zero were replaced with an epsilon value of 0.01, thereby maintaining the decline in demand. Similarly, negative values of historical demand, which are interpreted as merchandise returns, were also replaced by an epsilon value of 0.01.

4

Analysis & Implementation

4.1 Current Forecasting Method

This section explains the *as is* situation of the forecasting process of IKEA Components' retail equipment that will serve as a baseline to compare the proposed methods.

The existing forecasting process at IKEA Components consists of a hybrid forecasting that combines quantitative and qualitative methods. First, for the quantitative component, the traditional MA method is applied considering an n parameter of three periods extracted from the historical demand of the previous year. For example, to forecast the demand of SKU X in June 2025, the average demand is extracted of the months May, June, and July in 2024. By considering three periods of the previous year, reactivity is avoided while maintaining the potential impact of seasonality. However, a trend pattern can easily be overlooked.

For the qualitative component, once all SKUs are quantitative forecasted, the demand planner focuses on the top A SKUs based on the ABC classification. These forecasts are then manually assessed and adjusted. IKEA Components' ABC classification is determined by the volume and frequency of orders. The assessment is done based on the demand planner's criteria. These criteria include the planner experience and knowledge about the items specific characteristics, sales patterns, trends, sales activities and marketing inputs obtained primarily from the marketing team. According to the demand planner, these adjustments are necessary to improve the overall forecast accuracy.

In this thesis only the quantitative component of the current forecasting is analyzed and the results compared. Moving forward when the authors refer "current method" it will stand for the quantitative aspect of it.

4.2 Data Exploration & Insights

This section begins with an exploration of the primary data, the historical orders, and identifying demand patterns. The aim is to provide insights to IKEA Components regarding their SKUs' demand behavior.

Through the use of Williams's (1984) categorization, the demand patterns were analyzed and the SKUs were clustered considering the threshold established in Table

2.1. Figure 4.1 illustrates four quadrants, built by the interception between CV^2 and ADI thresholds, in which each quadrant represents a different pattern category. The horizontal axis measures demand variability, with SKUs on the left being more stable and those on the right more volatile, while the vertical axis shows the average interval between nonzero demand periods, where a lower ADI indicates frequent demand and a higher ADI signifies more intermittent demand. It should be noted that the Figure 4.1 had to be cropped for better visualization and several points remained outside the upper right quadrant.

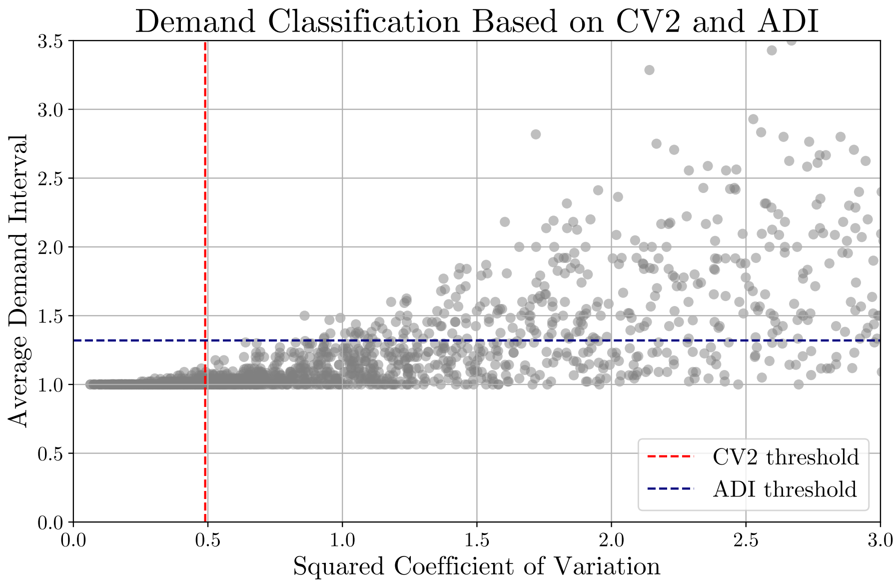

Figure 4.1: Squared Coefficient of Variation Vs Average Demand Interval.

In total 434 SKUs fell in the bottom-left quadrant (smooth), these SKUs have frequent and stable demand. In the bottom-right quadrant (erratic), 738 SKUs experience frequent but erratic demand. In the top left quadrant (intermittent), no SKU fits in this category of demand behavior that combines infrequent but stable demand size. Finally, in the top-right quadrant (lumpy), 667 SKUs face both infrequent and volatile demand. Table 4.1 summarizes the number of SKUs that follow the different patterns.

Table 4.1: Demand Pattern Classification

Demand Pattern	**Number of SKUs**
Smooth	434
Erratic	738
Lumpy	667

One take away from Figure 4.1 is the high demand variability exhibited by 76% of the total retail equipment that exceeds the CV^2 threshold giving a hint of the potential magnitude of the forecast errors.

As mentioned in the Literature Review Chapter, SKUs with lumpy demand are challenging to predict and require specialized forecasting techniques in hand with qualitative assessment to increase their forecast's accuracy. Therefore, the SKUs with this pattern are excluded to avoid deviations in the results. To understand the lumpiness of the demand more in-depth, Figure 4.2 illustrates a real example of a retail equipment demand that follows a lumpy pattern showing long periods of zero and very low demand followed by sudden spikes indicating highly irregular and nonpredictable sales.

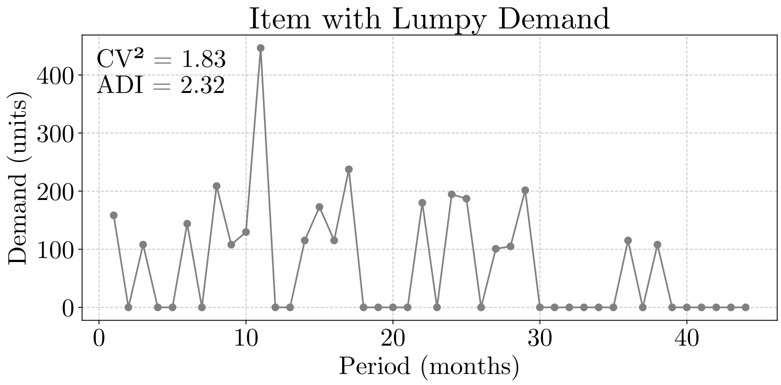

Figure 4.2: Example of an Item with Lumpy Demand.

4.3 Selection of Forecasting Methods

In this section, the rationale behind the choice of forecasting method is detailed. The analysis exclusively employs intrinsic methods rather than extrinsic ones since the latter method requires several explanatory variables that the retail equipment sales must be dependent on. According to Jonsson and Mattsson (2009), the use of extrinsic methods is recommended when the external variables are easy to forecast or at least easier to forecast than the forecasting variable itself. Furthermore, Jonsson and Mattsson (2009) also suggested that when the forecast variable is future sales, the best input variable is historical sales. In this study, historical sales for 48 periods were provided, serving as the most reliable predictor for future sales. Therefore, intrinsic methods are considered sufficient for the analysis.

The selection of forecasting methods is based on the current pool of methods that are well established in the literature but, most importantly, are available within the new IKEA Components ERP system. The following intrinsic forecasting methods have been selected for analysis: Moving Average, Single Exponential Smoothing, Double Exponential Smoothing, Triple Exponential Smoothing (Multiplicative and Additive), and Seasonal Smoothing (Multiplicative and Additive). It is important to note that the Croston method, although is widely recognized and frequently recommended for forecasting retail equipment, was not included in the assessment because the SKUs selected for forecast do not exhibit intermittent demand patterns, which are the primary target of the method. In Appendix I, a further discussion about this particular method is provided.

4.4 Selection of Evaluation Metrics

The MAPE is the main evaluation parameter used to compare how well the various forecasting methods perform. This choice enables consistency in communication between authors and IKEA Components when presenting the results, as MAPE is the current accuracy metric used by the company. Additionally, since it is a unit-free measurement, MAPE facilitates comparisons across several datasets making it possible to evaluate the forecasting accuracy of SKUs from different categories (Nahmias & Olsen, 2015).

4.5 Selection of the Optimal Forecasting Method

Microsoft Excel is used to store the historical demand data received from IKEA Components since it is possible for software packages to process the data from Excel sheets.

To calculate the demand forecast with the eight different forecasting methods, the software tool Python is used. The demand data for each SKU is read from Microsoft Excel using the function `read_excel()` from the Pandas library to store into a data frame. This function could take several data parameters like the path to data, sheet name, header, data type and many more (The Pandas Development Team, n.d.). Later on, using the data read from Microsoft Excel, each forecasting method is assessed by applying the formulas explained in the Literature Review Chapter.

To store data in a format that can be computed, arrays are created using the NumPy Python module. This library allows the creation of arrays with several dimensions and allows basic algebraic computations such as division and taking the absolute value (NumPy, n.d.). The Numpy library is used to retrieve the MAPE using the actual demand and the calculated forecast.

Different model parameters are tested using `for loops`. Python `for loops` allows the execution of the same process a fixed number of times, with the parameter to be defined being the number of repetitions (Python Software Foundation, n.d.).

For the MA Method, the number of periods n is limited to a maximum of 36 since the available demand periods are 48 and the MAPE is calculated over the last 12. Therefore 36 was the maximum number of periods that can be used for forecasting in January 2024. For the Holt-Winters methods, the range of smoothing parameter combinations was set to begin at 0.1 and increase in increments of 0.1 until 1. This approach is commonly applied, as increments smaller than 0.1 do not yield significant improvements in MAPE; however, they considerably increase the computational complexity.

For instance, for a TES method, the current approach evaluates the forecasting performance of $10^3 = 1000$ different parameter combinations per SKU (10 for each α, β, γ). If the increment were changed to 0.01, the algorithm would need to compare $100^3 = 1000000$ parameter combinations per SKU, which brings 1000 times more complexity. Considering the range of the retail equipment, the marginal improvement in MAPE does not justify the significantly increased computational burden.

The selection of 0 as a smoothing value is not allowed in order to prevent the algorithm from switching to another forecasting method. For instance, a TES model would become a SES method if β and γ were both set to 0. The choice of $\alpha = 1$ for the SES method is limited as well since it would yield the same result of MA when $n = 1$.

The logic behind the selection of the optimal smoothing parameters is based on the average MAPE over the last 12 periods of the forecast, where the parameter combination that yields the smallest MAPE is selected, stored in a data frame and saved in Microsoft Excel file for each SKU using the `to_excel()` function from Pandas library. The `to_excel()` function is useful for writing the output of the Python code by specifying the target file name as an input parameter (The Pandas Development Team, n.d.). See Table 4.2 for a representation of an output Excel file for the TES method.

Table 4.2: Example of Parameter Selection Result Excel Format

SKU	**MAPE**	**ALPHA**	**BETA**	**GAMMA**
XXX	16.87%	0.3	0.2	0.5

After the eight forecasting methods are executed for all SKUs, the files with the optimal parameter selections and MAPEs are compiled into a new Excel file. In this file the MAPEs are compared across the methods and the one that yields the lowest MAPE is identified for each SKU. Finally, a summary containing the SKU, best-performing method, selected parameters and MAPE is presented as a final deliverable to IKEA Components.

5
Results & Discussion

This chapter addresses the initial research question regarding which methods are the most accurate for predicting the demand for retail equipment within IKEA Components. Additionally, it presents findings and suggestions from the results and discusses the potential economic, environmental, and social implications of improvements in demand forecasting.

5.1 Results

After demand classification was completed and SKUs with lumpy demand were excluded from the analysis, the remaining items with smooth and erratic data were forecasted using the different forecasting methods proposed in the previous chapter. IKEA Component's current method was evaluated as well, to establish a baseline of the current forecast accuracy and enable comparison in case of improvement. In total, eight forecasting methods were assessed. To maximize the accuracy per method, an iterative process of parameter selection was done in which the parameters that yield the smallest MAPE for the last 12 months' forecasts were selected and recorded for each method and SKU. Then, the MAPE was compared across the different methods to decide the optimal one for each SKU.

To better illustrate how each forecasting method captures with the actual demand, Figures 5.1 and 5.2 were plotted. The figures compare the actual demand to the current and proposed forecast for two sample SKUs with smooth and erratic demand. In the case of the erratic item in Figure 5.1, the TES Additive method stands out for its ability to closely follow the sharp fluctuations in demand. In contrast, simpler models such as MA and the current method tend to underpredict during peaks, while multiplicative methods such as SS and TES tend to overpredict the demand.

In the case of the smooth item in Figure 5.2, the differences among methods are more subtle. Surprisingly, the MA method performs well given its computational simplicity demonstrating that even basic approaches can be effective under stable demand conditions.

Table 5.1 presents a summary of the best-performing forecasting methods for all SKUs based on their demand patterns. Among the evaluated methods, DES method seems to be the most effective method among all. Similarly, TES (Additive) performs well for 179 erratic SKUs and 69 smooth SKUs that represent 21% of total SKUs. The MA method and the current method had covering 17% and 13% of

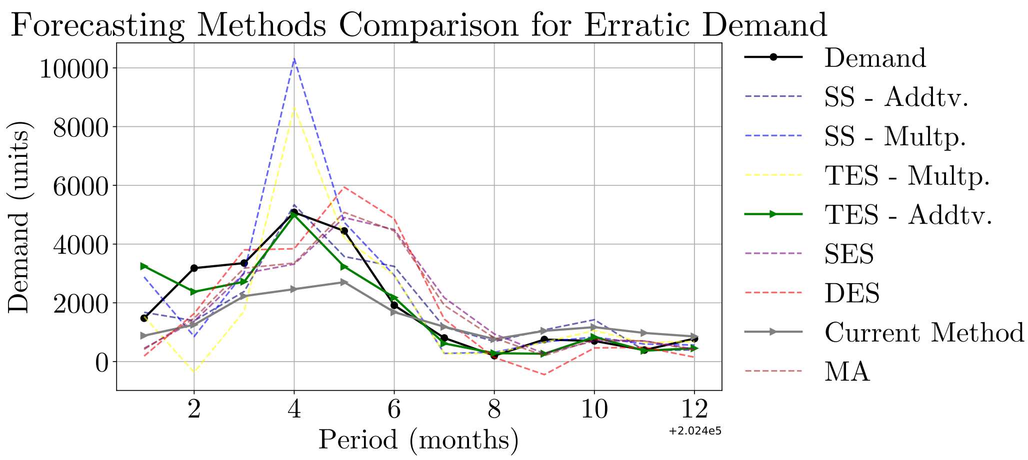

Figure 5.1: Forecast Comparison for an SKU with Erratic Demand using Different Forecasting Methods over the last 12-month period.

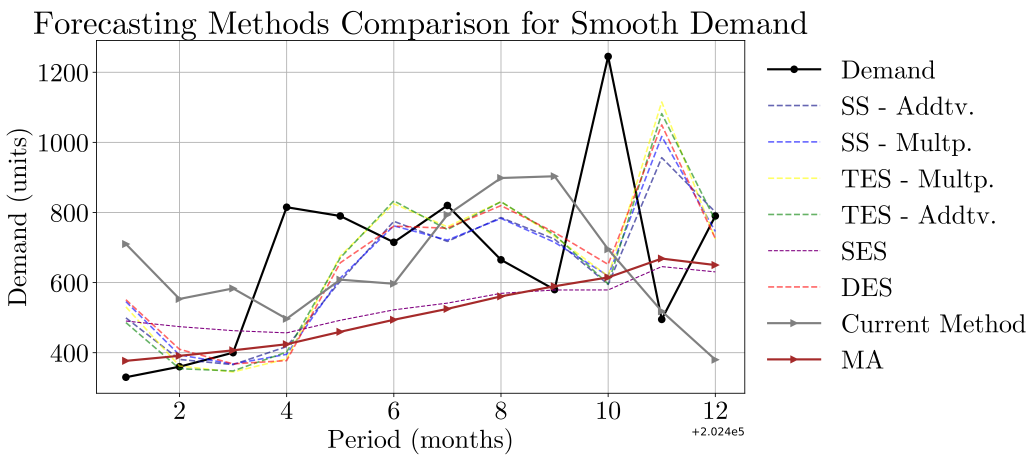

Figure 5.2: Forecast Comparison for an SKU with Smooth Demand using Different Forecasting Methods over the last 12-month period.

SKUs, respectively. Interestingly, SES showed limited applicability, being the best method for only 1% of the time. The remaining methods, SS (both Additive and Multiplicative) and TES Multiplicative were moderately effective in 5% and 13% of cases.

Furthermore, based on the results shown in Table 5.1, several insights were drawn. First, since the current method was chosen as the best-performing method for only about 13% of all SKUs, the validity of this study's problem statement is demonstrated. In other words, the results show that at least one of the suggested forecasting methods brought improvement for almost 87% of the erratic and smooth SKUs. At the same time, the dispersion among the different methods proves that the *one size fits all* approach is not suitable for the retail equipment.

Another observation from Table 5.1 is the popularity of the MA method across both smooth and erratic SKUs. Despite being the least computationally intensive method to execute among the selected forecasting methods, it yields satisfactory results for

Table 5.1: Distribution of Best-Performing Forecasting Methods per Demand Category

Best-Performing Forecasting Methods	Number of Erratic SKUs	Number of Smooth SKUs	Percentage
Moving Average	119	86	17%
Simple Exponential Smoothing	5	6	1%
Double Exponential Smoothing	168	82	21%
Seasonal Smoothing (Additive)	53	34	7%
Seasonal Smoothing (Multiplicative)	19	45	5%
Triple Exponential Smoothing (Additive)	179	69	21%
Triple Exponential Smoothing (Multiplicative)	98	52	13%
Current Method	97	61	13%

the retail equipment at IKEA Components. The SES method was introduced as an alternative method for stationary demand patterns alongside MA; however, it was the method that achieved the lowest forecasting error for only 1% of the SKUs. Although the SES has a more sophisticated smoothing approach, MA proved to be a sufficiently effective alternative for the behavior of this dataset.

5.2 Comparison of Forecasting Errors

Once the the best performing method for each SKU was determined, it was important to measure the improvement brought with the new methods compared to the *as is* scenario. This measurement provided a basis to evaluate the criticality of implementation of the suggested forecasting methods and used them as a basis for future decision making for IKEA Components. More accurate forecasts are expected to inform inventory management decisions like stock planning, replenishment amount/frequency and so on.

It is important to note that the historical data used in the statistical forecasting was based on the placed orders. As explained by Jonsson and Mattsson (2009), order quantity cannot be always interpreted to be the actual representation of the real demand. There could be several scenarios why orders are different than the actual demand, and these scenarios inevitably would impact the error rates as well. For instance franchisee's initiatives to keep stocks for critical or high lead time items could motivate them to order more than their actual needs. Another possibility is IKEA Components being stock out for a specific item could result in a smaller order quantity than the actual need. Therefore, it is necessary to recognize that forecast errors will occur even with the most appropriate methods and it should always be interpreted in the business context.

Table 5.2 shows the average MAPE values for both the current and best-performing forecasting methods across all SKUs. Because erratic SKUs tend to have much higher forecast errors by nature, the values were analyzed separately for erratic and smooth SKUs to allow for a valid comparison. The results reveal a substantial improvement where the best-performing methods reduced the average MAPE by approximately 84% for erratic SKUs (from 39304% to 6307%), and by 97% for smooth SKUs (from 2208% to 56%).

Table 5.2: Average Forecast Error Comparison between Current Method and Best-Performing Method

Demand Pattern	**Current Method (%)**	**Best-Performing Method (%)**	**Error Reduction (%)**
Erratic	39304	6307	84
Smooth	2208	56	98

To better understand how the errors are distributed, a further analysis was conducted by plotting them. The box-plots in Figures 5.3 and 5.4 compare the distribution of MAPE errors for goods with erratic and smooth demand in two scenarios: the best-performing method and the current method. These visuals are presented to show the dispersion of the error and to identify the outliers that deviate the means.

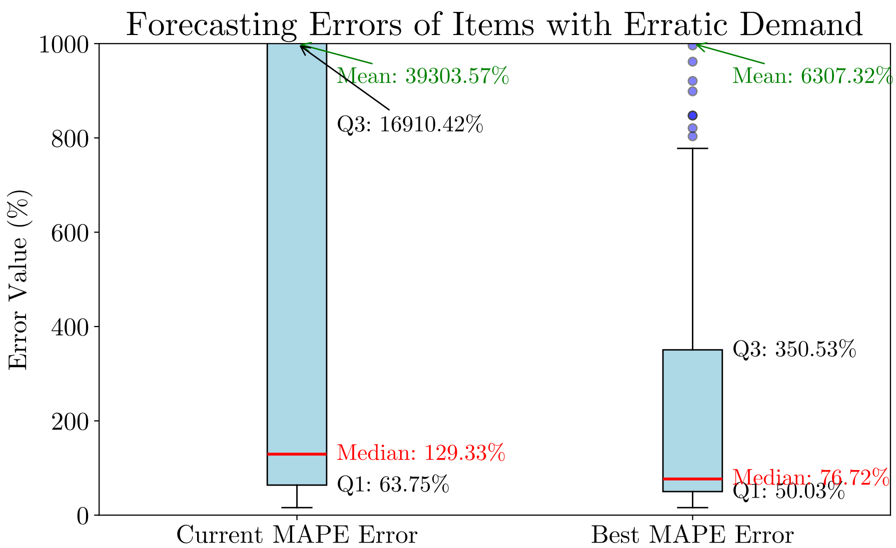

Figure 5.3: Comparison between Current and Best-Performing Forecasting Method Errors of Erratic Items.

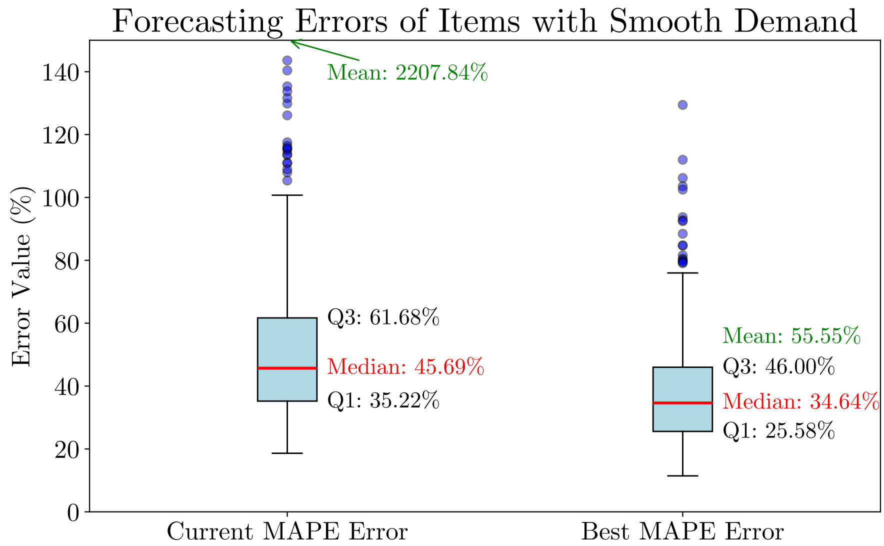

Figure 5.4: Comparison between Current Method and Best-Performing Method errors of Smooth Items.

In both figures the distribution of errors of the current method had to be cropped for a better visibility of the errors of the improved methods. The red line indicates the median value, which represents the value situated in the middle of the dataset; while the first and third quartiles, which indicate the range within which the majority of values fall. As can be noted, in all cases the means fall outside the light blue bracket, suggesting that the mean does not accurately describe the dataset behavior.

Figure 5.3 shows how the error range of the current forecasting method for erratic items is very large, ranging from 63.75%, which is the first quartile (Q1), to 16910.42%, the third quartile (Q3). However, the median of 129.33% shows how the outliers distort the distribution. On the other hand, when observing the distribution of errors of the best-performing methods, one can observe a much narrower inter-quartile range spread, from 50.08% (Q1) to 350.53% (Q3), with a reduced median error of 76.72%. The new median value shows that half of the forecasts fall below 76.72% which proves the significance of the improvement. The decrease of the mean from 39303% to 6307% also shows that the improvement in severe circumstances are still non-ignorable even when the values were skewed by extreme outliers. These changes in mean, median, and inter-quartile ranges prove the efficacy of the new methods.

A similar fashion can be observed for smooth items in Figure 5.4. The median error dropped from 45.69% to 34.64%, the inter-quartile range reduced with Q1 shifting from 35.22% to 25.58% and Q3 from 61.68% to 46.00%. These results indicate a noticeable increase in the forecasting accuracy. The new inter-quartile range reflect a concentration of errors around lower values. Last but not least, the mean error dropped dramatically from 2208% to 56%, indicating an increase in average performance despite the distorting caused by outliers.

Overall, in both cases, whether for smooth or erratic items, the best method demonstrates a significant improvement in forecasting accuracy, as evidenced by a lower median error, a lower mean error, and reduced overall dispersion. However, from the figures, it can be seen that there are still some cases with extreme forecasting errors that should be investigated further with a case-by-case approach through qualitative assessment. In Section 5.4, suggestions on how to approach this assessment are described.

5.3 Findings

This section presents two key findings that emerged from the analysis conducted in this study. First, it explores the demand patterns identified based on the selection of the most effective forecasting methods. Second, it examines the correlation between the different categories of retail equipment, based on the selection of those same methods. Together, these findings offer a deeper understanding of both demand behavior and category-level dynamics within retail equipment.

One interesting insight from the results is that the distribution of SKUs across forecasting methods provides insights into the behavioral patterns of the item's demand. As explained in the Literature Review Chapter, each forecasting method is theoretically better suited to specific types of demand patterns. Table 5.3 presents the suggested forecasting methods for each demand category. The demand pattern that involves the largest portion of SKUs is trend and seasonality occurring simultaneously. Refer to Figure 5.5 for the distribution of the SKUs demand patterns based on the best-performing forecasting methods.

Table 5.3: Demand Pattern Assignment by Forecasting Method

Forecasting Method	**Demand Pattern**
Moving Average	Stationary
Simple Exponential Smoothing	Stationary
Double Exponential Smoothing	Trend
Seasonal Smoothing (Additive)	Seasonality
Seasonal Smoothing (Multiplicative)	Seasonality
Triple Exponential Smoothing (Additive)	Trend + Seasonality
Triple Exponential Smoothing (Multiplicative)	Trend + Seasonality
Current Method	N/A

The current method is considered separately from the others, and no specific demand pattern was assigned to it, as it is not a scientifically established method designed for a particular demand behavior. One can consider it as a seasonal MA method since it utilizes a three-month average from the previous year. However, the method does not account for recent periods, as the MA method does, and does not smooth the seasonal fluctuations like the SS methods. Consequently, no specific demand pattern could be assigned to the SKUs forecasted using this method, therefore it is presented as "N/A", standing for "Non Applicable" in the Figure 5.5.

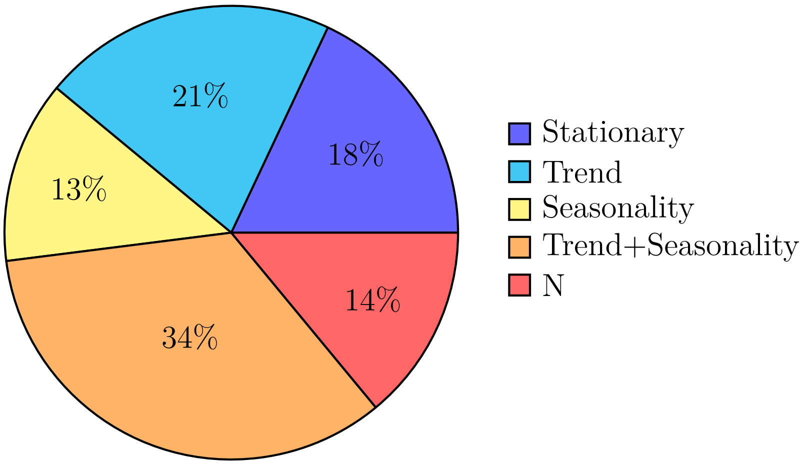

Figure 5.5: Distribution of Demand Patterns based on Forecasting Method Selection.

The MA method is theoretically recommended for application to stationary demands. However, in this study it was determined that this premise is not always met, and that the factor indicating this is the parameter n yielding the lowest forecast error. In the study, when a lower n was identified as optimal, it suggested that a more reactive forecast is advantageous, potentially due to a changing trend in recent periods. This supports Jonsson and Mattsson's (2009) argument in the literature that, as the parameter n increases, the forecast becomes less reactive to fluctuations or outliers causing these irregularities to dissipate.

To explore this, the forecast results using the MA method were observed to note the difference between forecasts with different n values. Figure 5.6 illustrates an example of an SKU demand and its forecasts applying MA method with n values of 24, 16, and 7 periods. In the example, an increase in consumption is observed in the last seven periods, with a particularly high peak in period 22. The forecast with n equal to 7 is more reactive to the positive demand trend and, therefore, more accurate for this example. This suggests that for items with a trend in demand, using a lower n is more optimal when using the MA method to forecast.

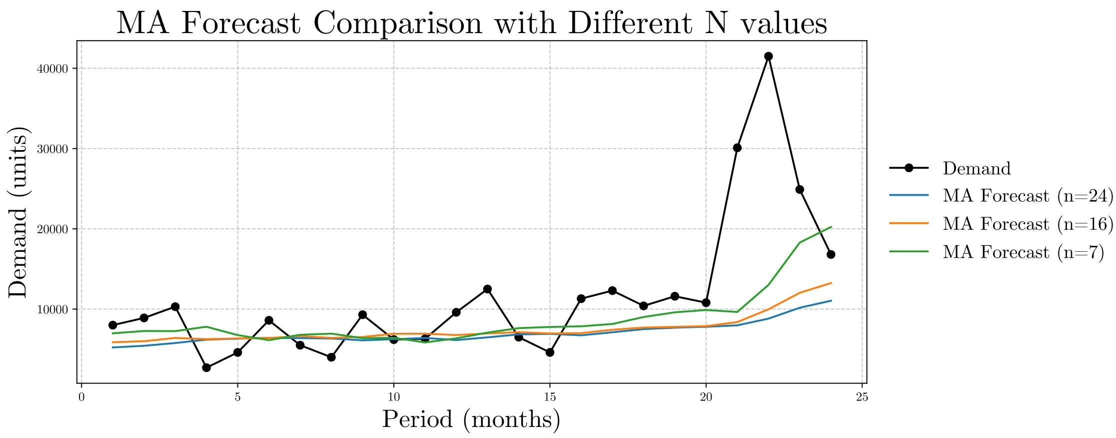

Figure 5.6: Example of an SKU Demand and Forecast applying MA Method with different N values.

To describe the behavior of this group of SKUs, the distribution of optimal n values was investigated where MA was the best-performing method. The results showed that 86% of these SKUs had an optimal n greater than 10 periods. Therefore, this finding supports the claim that, within this data set, the selection of the MA method reflects stationary demand behavior.

Grouping forecasting methods based on demand patterns is essential for gaining a clearer understanding of the overall demand behavior of the products. For example, SES and MA were included in the method selection to provide alternative options for SKUs with stationary demand. Recognizing demand patterns can significantly enhance the replenishment process for retail equipment. For instance, knowing that 34% of smooth and erratic SKUs exhibit both trend and seasonality can help tailor inventory policies more effectively. This understanding also allows for better alignment of KPIs; for example, during periods of naturally low demand, maintaining low stock levels should not be penalized. Similarly, if 21% of SKUs show a clear trend, forecasts for these items should be reviewed frequently to ensure that replenishment aligns with increasing sales.

Another interesting finding, as a result of crossing the forecast results that best predict different SKUs demand with the data containing the items categories (based on their functional classification), is the strong correlation observed between certain subcategories. The TES Additive method is the one that best predicts the behavior of items in the subcategories of Cable, Indoor Lighting, Floor Standing Solutions, and Shelving. When plotting the demand data, it can be observed that the four subcategories have a behavior pattern that includes a similar proportion of positive year-over-year trends and a consistent seasonal pattern, meaning that there are sales peaks and drops in the same months of the year. To support this statement, a correlation analysis is conducted among the demands of all the subcategories. Figure 5.7 shows the correlation values, in which it is evident that the four subcategories are strongly correlated.

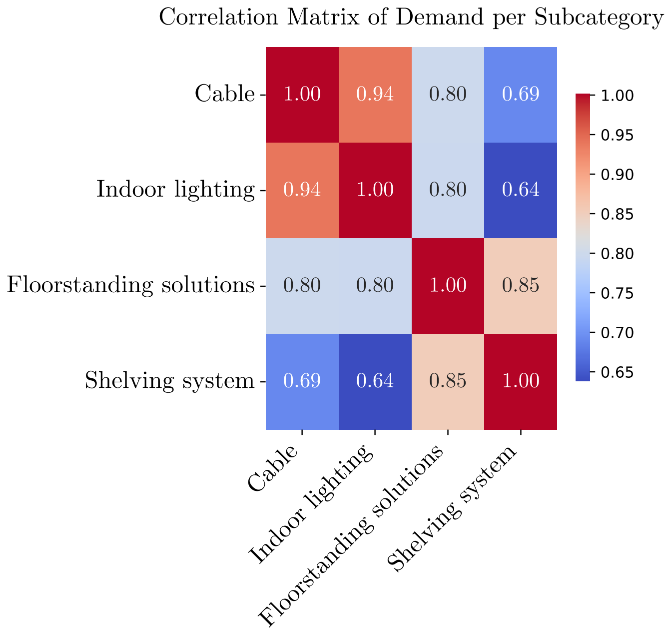

Figure 5.7: Correlation Matrix between Subcategories: Cable, Indoor lighting, Floor Standing Solutions, and Shelving

Under the same analysis, the four subcategories, Basic Racking White, Ceiling Mounted Solutions, Cookware & Tableware, and Textiles have a high percentage of SKUs for which the best-performing forecasting method is the TES Additive. The four categories follow a similar pattern of sustained year-over-year sales growth and display a seasonal pattern with frequent sales peaks in March and April and sales drops between October and December. This suggests a high-demand season at the end of the first quarter and the beginning of the second, while towards the end of the year, especially in December, significant drops in demand are observed. Figure 5.8 shows the strong correlation between the subcategories, supporting the selection of the TES forecasting Method for the majority of the SKUs within the subcategories.

These findings may have implications for inventory management. The strong correlation suggests that, rather than treating each subcategory in isolation, the demand planner could forecast them in an aggregated manner to reduce uncertainty. Additionally, orders could be consolidated and replenishment actions coordinated jointly, optimizing resources. In summary, these findings offer practical insights that can transform the way inventory is managed and demand is planned in the identified subcategories.

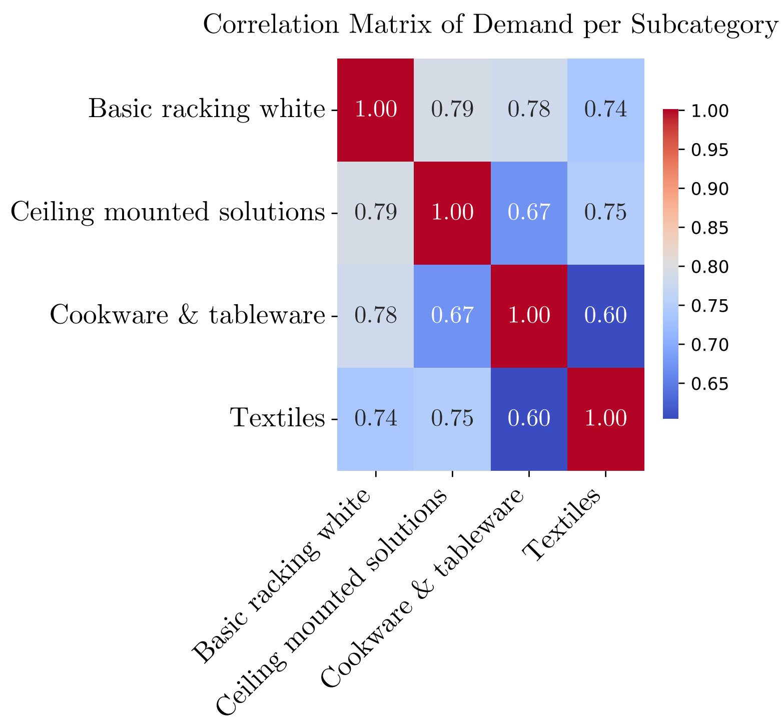

Figure 5.8: Correlation Matrix between Subcategories: Basic Racking White, Ceiling Mounted Solutions, Cookware & Tableware, and Textile

5.4 Qualitative Assessment Suggestions

As mentioned in the Methodology Chapter, the scope of this study was limited to quantitative forecasting evaluations. By the nature of this master thesis study, the authors' aim was to suggest the most suitable forecasting algorithm for the retail equipment within the capabilities of IKEA Components' ERP system. The analysis was based on the historical demand data; therefore, the results of statistical forecast represents only a discovery of patterns based on the available data, as suggested by Nahmias and Olsen (2015). Therefore the results of statistical forecast cannot be judged by the authors qualitatively due to lack of information in terms of company insights and future projects, and confidentiality. It was explained by the demand planner that IKEA Component's current statistical model is continuously revisited to identify any outliers and to smooth the forecast using their market knowledge and experience. This process significantly increases the accuracy of the final forecast for them.

Using the suitable forecasting methods brought remarkable improvement in terms of forecast accuracy as explained in section 5.2, which brings the question mark of whether the accuracy could be further improved by the integration of qualitative forecasting. It is important to revisit the business model of IKEA Components before judging the possibility of qualitative methods according to the conventional business models. Suggestions are based on the observations made during the visits to IKEA Components.

There exists no traditional sales team in IKEA Components that promotes retail equipment to their franchisees. Their primary goal is not to hit a specific sales volume, even if they want to build strong relationships with their clients. Instead, they work as an internal supporting market organization securing procurement process with the goal to avoid unnecessary cost for IKEA. On the other hand, there are certain products that the franchisees are obliged to purchase for the CMP from IKEA Components to preserve the brand identity. Therefore, a method like Sales Force Composites is not suitable for IKEA Components because of the structural difference from a traditional selling organization.

Customer surveys on the other hand, could be explored in the IKEA Components' context as the insights on the projects are the most important piece of information for them. A well-timed flow of information about a store opening or a project execution would increase the forecast accuracy, as this events cannot be identified through time series data and no algorithm is currently in place to identify them from demand patterns. Although the retail equipment business is small in terms of volume within the IKEA Components organization, its criticality of the business is high, as it contributes to IKEA expansion and the product range is the backbone of store operations. Therefore, a smooth flow of information could only be for mutual benefit both IKEA Components and their franchisees.

The CPFR concept explained in the Literature Review Chapter was found suitable in this study, as such collaboration will benefit each party. Creating a joint forecast could push franchisees to stick long-term planning rather than last-minute project executions. This collaboration will essentially benefit the customer side since they will receive a higher service level thanks to the increased available time for IKEA Components to plan the replenishment. KPIs like on-time delivery could benefit from measuring the service level and convincing the customer of the importance of timely information sharing. Co-sharing the risks is also crucial for the trust dynamic between the parties.

It was observed that a modified version of the Jury of Executive Opinion model could be applied to IKEA Components. Regular meetings of the strategic departments could be an opportunity for internal information flow. According to the market manager, franchisees should go into the long process of approvals if for some reason they would like to purchase a mandatory range article from another seller. If this information can be translated to volume, the forecast may be modified accordingly to increase the accuracy.

When it comes to the Delphi Method, the authors could not identify a reason to anonymize the insights from different departments to prevent possible overshadowing of opinions among the individuals. Transparency and collaboration are at high levels as the main focus of the organization is internal support rather than profitability.

5.5 Implications on Forecast Improvement

Improving forecast accuracy creates a snowball effect throughout the supply chain. This impacts the economic, environmental, and social aspects in particular, and this is what is explored in more detail below.

5.5.1 Economical Implications on Forecast Improvement

In the current dynamic market context, accurate demand forecasting is a critical enabler for companies to make informed decisions, increase service level, better manage their inventory, and rival among their competitors therefore have an overall better financial performance (Veiga et al., 2010).

An accurate forecast is necessary in order to respond to client demand in a timely manner. In case of systematic underestimation of the demand service level lessens leading to an increase in the total cost (Xie et al., 2004). Veiga et al. (2010) also proved that an accurate forecast has a direct impact on the service level and financial performance of a company.

Deficient inventory, excess stock, and backlogs are the results of a mismatch between forecast and demand leading to negative impacts on a company's cash flow (Veiga et al., 2010). Companies can improve their inventory management thanks to the quality information flow from demand management which will reduce the capital tied to finished, work in progress, and raw inventory (Veiga et al., 2010). In IKEA Component's case, since they are not involved in the production of the retail equipment, savings will be reflected in sourcing processes instead.

5.5.2 Environmental & Social Implications on Forecast Improvement

The main aim of this thesis was to identify the demand behavior of retail equipment of IKEA Components and come up with forecasting method suggestions to eventually help them improve their operations. Although accurate forecast and demand management is fundamental for a company's decision-making process, as discussed in the Literature Review Chapter, it has many other underlying benefits that come with it. The sustainability impact of a company resulting from its operations has a considerable influence on its success in demand management (Agatz & Fleischmann, 2023).

The improvement brought thanks to this study would ultimately reduce the environmental impact in sourcing, inventory management, and transportation to customer stages as IKEA Components do not produce retail equipment themselves. Agatz and Fleischmann (2023) argue that supplier activities, delivery of the goods, and transportation are the three emission resources for a company's sourcing operation. Retail equipment is sourced from several suppliers and stored in IKEA warehouses, therefore accurate forecasting would reduce emissions resulting from excess stock, excess transportation, and waste management. Another argument regarding the delivery processes could be that accurate demand management reduces the need for high-emission transport solutions to customers like air freight, choice of mode of transport could change sustainability impact due to lead time constraints. One can say that effective forecasting may greatly reduce the overproduction that resulted from IKEA Components' incorrect demand projection, even though the direct impact on the suppliers' own operations and production cannot be calculated. Timely and accurate forecasts may even impact IKEA Component's choice of sustainable supplier and transportation options for both inbound and outbound flow. Another relevant environmental impact is on waste management caused by excess stock, as it implies not only material, energy, production, and transport efforts for that stock were wasted but there will be even more to process that waste (Agatz & Fleischmann, 2023).

According to The Global Reporting Initiative (2013), the social aspect of sustainability is the effect of an organization on the social environments and communities it operates in. The importance of sustainability in business operations is only becoming bigger over time therefore companies' liability and accountability increases. There is a growing trend in requirements from authorities, stakeholders, and non-governmental organizations (NGOs) in terms of companies' responsibilities (Agatz & Fleischmann, 2023). In this study's context, the result of improved demand management is expected to reduce the waste generated due to the gap between production and demand. The emissions connected to retail equipment and waste generated are not currently addressed by IKEA (Inter IKEA Group, 2025). As explained in the Literature Review Chapter, waste management is an area for companies to have relatively lower control due to the difficulty of calculating indirect impact, and it is an area that concerns the social sustainability pillar due to its impacts on disadvantaged societies. Since waste management is a service that is outsourced, what companies can do is to impact the end of their processes by generating less waste. The more accurate the demand forecasting, the smaller the gap between production and demand, therefore the less waste generated.

In conclusion, sustainability is an area that cannot be separated from any business goal of today, therefore it was worth mentioning the positive impacts of this work on IKEA Component's sustainability impact. Accurate demand forecasting is expected to benefit from reducing emissions by reducing overproduction, transport, inventory holding, and usage of unsustainable freight options.

6

Conclusion and Implications

6.1 Conclusion

This thesis study was designed to increase the forecast accuracy for retail equipment of IKEA Components by testing several forecasting algorithms among the well-known methods in the theory. The chosen eight different forecasting algorithms were tested out with alternating parameters to iteratively enhance accuracy and select the best-performing method-parameter combinations for each SKU. The error measure MAPE was used to compare the performance of different methods and the parameters.

The new suggested methods brought improvement for almost 90% of the scope compared to the previous method used by IKEA Components, also defined as the "current method" in the previous chapters. DES and TES (Additive) were the two methods standing out by being the best-performing methods for 42% of the scope. The current method outperformed the remaining methods for 13% of the time, indicating the significance of keeping the method in the scope for the future. Having each suggested method yield the smallest error for at least one SKU validates the importance of testing diverse forecasting methods for the relevant study. Apart from the SES, every proposed method performed the best for a non-negligible amount of SKUs, indicating the selection of the methods was successful.

The SKUs were classified under two sub-categories as erratic and smooth to demonstrate the results clearly and avoid irregular demand behaviours overshadowing the improvements. Forecast error reduced to 6307% from 39304% for erratic demand pattern products and to 56% from 2028% for the smooth demand pattern products. As the means were distorted by outliers, Figures 5.3 and 5.4 were presented to illustrate the distribution of errors and improvements on the medians as well. The introduction of the new methods changed the game for retail equipment accuracy, and the improvements were addressed from several perspectives.

Several methods were suggested to cover different demand patterns, and the selections were based on which type of demand pattern they were suggested for in the theory. Figure 5.5 was plotted to understand the emerging demand patterns in the data, and the combination of trend plus seasonality had the biggest portion in the pie chart, proving the importance of TES methods.

Furthermore, although the quantitative methods brought significant improvements in the accuracy, by the needs of IKEA Components, authors explored the applicability of the qualitative methods. Customer surveys and a modified version of

Jury of Executive Opinion methods were found suitable to foster and gain from collaboration.

Finally, as today's supply chain management students and future professionals, the authors found it crucial to mention the sustainability impacts of this study. It was shown that the forecast accuracy improvement could positively impact sustainability in all triple bottom lines.

6.2 Implications

6.2.1 Managerial Implications

Basing this research on a case study with real historical data provides a foundation for companies who aim to improve their demand forecasting process for retail equipment or for products with similar demand behavior. Furthermore, the authors provide a step-by-step analysis methodology to help companies facing the same challenges find a path to resolution.

An important aspect that companies must examine is the characteristics of their product range, as it is a fundamental step in correctly selecting and implementing the most appropriate methods. In the case of IKEA Components, which has a wide range of products, it was not possible to evaluate each SKU individually, which is why it was crucial to have several forecasting methods to cover the different demand patterns.

A crucial and often underestimated step prior to analysis is data preprocessing. In this research, this step was not linear. Initially, data cleaning was performed, but as the analysis progressed, certain inconsistencies were discovered that needed to be corrected. It is important for practitioners to be aware that not all data sets will have the same inconsistencies. This depends greatly on the source providing the information. However, it is important to perform this step with great caution, as data quality is crucial for comparing results.

Furthermore, although it was limited to some extent, the importance of qualitative forecasting has already been mentioned. This is especially true for products for which there is insufficient historical demand or internal insights about upcoming projects that could affect demand. This demonstrates the importance of strong communication between customers (internal and external) and the focal companies.

Moreover, as mentioned in the beginning of the thesis, the current supply chain disruptions create shifts in consumer behavior changing demand patterns over time. Therefore, it is important for businesses to regularly review the allocation of method-parameter combinations to stay aligned with the dynamic market conditions.

6.2.2 Research Implications

This study provides to researchers a unique, real-life example of improved demand forecasting for store products that are not directly consumed by customers in a retail context. Similar business model examples are scarce in the literature, so this study fills a gap in the literature and provides a foundation for future research on the forecasting demand for products with similar characteristics.

This thesis also offers a theoretical analysis of the economic, environmental, and social implications of increasing the accuracy of demand forecasting for retail equipment. These findings invite researchers to analyze the impacts more broadly and pave the way for further research on the relationship between demand planning and sustainability goals in the retail sector.

Another contribution to science of this thesis is the framework (see Figure 3.1) created as a methodology to process the input information, which is the historical demand for items, analyze it, and obtain results indicating the best methods and parameters to forecast this demand. This methodology can be used as a guide and adapted by other researchers in similar studies. Within the framework, the item clustering step is fundamental to defining the scope of the analysis and selecting the forecasting methods. In this thesis, variance partitioning was used as a technique to classify the items, which allowed a better interpretation of results, but it is not the only way to do so. This approach is not necessarily exclusive; other classification techniques can be incorporated, thus opening the door to new research that explores other alternatives but within the same framework.

6.3 Future Research

Due to its nature, this study is subject to time and resource constraints. Therefore, this section hopes to shed light on different avenues that this thesis can lead to for future research. These avenues could be either to expand the methodology or to measure the consequences of the results.

First, a limited number of methods widely recognized in the literature were applied. This was due to the limited time available and since, due to confidentiality issues, variables such as price could not be included in the analysis. These limitations open opportunities for future research to predict retail equipment demand with different variables and test state-of-the-art and more complex forecasting methods alongside qualitative forecasting integration.

Second, Chapter 4 established the importance of frequently reviewing the forecast because demand patterns are constantly changing. However, future research could explore the periodicity of this review in greater detail and define it according to criteria such as the criticality of the product (considering its ABC classification) or the volatility of its demand.

Third, since demand forecasting is an upstream step in the inventory management process, it is difficult to accurately determine the implications of improving it. Chapter 5 theoretically outlined the potential economic, environmental and social implications of increasing forecast accuracy. However, without an experimental analysis, it is difficult to demonstrate the specific areas that would be affected and to what extent. Future research could empirically investigate the real impact of these improvements once the new methods are implemented.

Before concluding, it is important to emphasize that, while this thesis was designed to provide valuable insights into demand forecasting, its scope was limited to IKEA Components' retail equipment, so the results cannot be fully generalized. This is due to the specific characteristics of IKEA Components' business model and the application niche of retail equipment.

In conclusion, this thesis demonstrates the vital importance of creating a reliable demand forecast, as it serves as a key input throughout the entire replenishment process. It also shows how improving forecast accuracy can positively impact various areas of the supply chain, making it more efficient and sustainable. In doing so, this thesis contributes to making more informed decisions and support the development of a more resilient supply chain. As the market expands, it becomes fundamental to maintain a robust supply chain that is adaptable, reliable, and effective.

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A

Appendix

A.0.1 Assessing Forecasting Methods for Lumpy Items

In this section, it is elaborated in greater detail the reasons behind why the Croston Method was considered in the theory but not in practice within the pool of evaluated forecasting methods. As explained in the Literature Review Chapter, this method is suitable for products with intermittent demand, as it applies separate exponential techniques to forecast both the demand size and the intervals between demands, and then divides these estimates to derive the average demand per period. It was selected for theoretical analysis because it has low computational overhead and is highly recommended in operation and production literature for forecasting spare parts (Willemain et al., 1994). Moreover, Croston is also in IKEA Components' interest to analyze a broad spectrum of forecasting methods as possible within its ERP pool of methods.

No item comes inside the top left quadrant, which is categorised as intermittent, with a CV^2 larger than 1.32 and an ADI below 0.49, as shown in Figure 4.1, which depicts the behaviour of retail equipment SKUs. However, given that nearly 40% of all retail equipment demonstrate lumpy demand behavior, characterized by irregular purchase orders not only in occurrence but especially in magnitude, it was determined that these items should be excluded from the main analysis, analyzed separately, and evaluated using the proposed methods alongside Croston.

For this analysis, the forecast error was assessed using the MSE as the MAPE formula involves dividing the absolute error by the actual value. When the actual value is zero, this division becomes undefined or infinite, which distorts the error calculation. This issue is especially critical in time series with intermittent or lumpy demand, where periods of zero demand are frequent. By using MSE, this limitation is avoided, as the difference between the forecast and actual values is calculated and then squared, without the need for division.

To compare and determine the best forecasting method, pairwise comparisons are performed between methods for each SKU, and the method with the smallest MSE is selected. MSE provides a consistent metric even when demand is zero, allowing for a fair comparison of different methods without disproportionately penalizing certain methods due to demand irregularities. Since MSE values are not comparable across SKUs, Table A.1 presents only the number of items for which each proposed method yielded the lowest forecast error.

In conclusion, the results in Table A.1 shows that 56% of the total of SKUs perform

Table A.1: Total Number of Forecasting Method Selection for Lumpy Items

Forecasting Methods	**Number of SKUs**	**Percentage**
Croston	372	56%
Moving Average	104	16%
Simple Exponential Smoothing	5	1%
Double Exponential Smoothing	27	4%
Seasonal Smoothing (Additive)	25	1%
Seasonal Smoothing (Multiplicative)	16	2%
Triple Exponential Smoothing (Additive)	13	2%
Triple Exponential Smoothing (Multiplicative)	86	13%
Current Method	19	3%

better with the Croston Method. Compared with the current method that only outperforms in 3% of lumpy SKUs, these results show an important improvement for the remaining 97% of SKUs.

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF SUPPLY AND OPERATIONS MANAGEMENT
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden

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