



Integrating Demand Forecasting and Inventory Policy for Home Textile Products under Limited Historical Data: Evidence from a Bed Linen Manufacturer

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Abstract

Demand uncertainty remains a critical challenge for textile manufacturers, particularly for bed linen products that vary in size, design, consumer preference, promotional cycles, and seasonal demand patterns. In practice, inaccurate demand planning may lead to excessive finished goods inventory or, conversely, stockouts that reduce sales opportunities and customer service performance. This study aims to develop an integrated model that links demand forecasting with inventory policy for bed linen products at PT XYZ. The study uses weekly sales and inventory data for seven bed linen size variants from August 2024 to June 2025. The research process includes exploratory demand analysis, demand pattern classification, time series forecasting model development, forecast accuracy evaluation, and the integration of forecasting outputs into inventory control decisions through safety stock and reorder point calculations. Several classical time series forecasting methods, including Moving Average, Exponential Smoothing, Holt Winters, and ARIMA/SARIMA, are compared using MAE, MAPE, and RMSE. Due to the limited historical dataset, rolling origin cross validation is applied to obtain a more reliable model evaluation. The proposed framework is expected to identify the most suitable forecasting method for each demand pattern and provide a more structured basis for inventory decision making. By integrating forecasting results into inventory policy, this study is expected to help reduce overstock and stockout risks, improve service level, and support more adaptive production planning in the textile manufacturing context.

Introduction

Demand uncertainty remains one of the most persistent challenges in manufacturing and supply chain planning, particularly in industries characterized by high product variety, short response cycles, and rapidly changing consumer preferences. In textile and fashion related sectors, demand is rarely stable because purchasing behavior is influenced by product design, size variation, promotion intensity, seasonal events, and channel specific market dynamics (Kourentzes et al., 2020; Abolghasemi et al., 2020). This challenge is not limited to apparel products. Home textile products, such as bed linen, also exhibit demand characteristics that combine functional replacement needs with aesthetic and fashion driven preferences. As a result, manufacturers must simultaneously avoid excessive finished goods inventory and

maintain sufficient stock availability to prevent lost sales and service failure (Gonçalves et al., 2020; Barros et al., 2021).

In practice, inaccurate demand planning can create two opposing but equally costly outcomes. Overestimation of demand leads to overproduction, high inventory holding costs, warehouse congestion, and capital tied up in slow moving products. Conversely, underestimation increases the risk of stockout, lost sales, production urgency, and declining customer satisfaction (Pinçe et al., 2021; Goltsoş et al., 2022). These consequences become more critical when a company manages multiple stock keeping units (SKUs) with different demand patterns. For products such as bed linen, demand may vary substantially across size variants, while promotional events and seasonal consumption cycles may generate sudden demand peaks that are difficult to capture using intuition based planning alone (Zhuang et al., 2022; Mediavilla et al., 2022).

Demand forecasting has therefore become a central component of data driven production and inventory planning. Classical time series methods, such as moving average, exponential smoothing, Holt Winters, and ARIMA/SARIMA, remain widely used because they are interpretable, relatively easy to implement, and suitable for short to medium historical datasets (Kourentzes et al., 2020; Svetunkov & Boylan, 2023). At the same time, recent studies show that more advanced machine learning and deep learning models can improve forecasting performance when larger and richer datasets are available (Seyedan et al., 2023; Tadayonrad & Ndiaye, 2023). However, in many small and medium sized manufacturing contexts, historical sales data are often limited, making classical statistical models still relevant as practical forecasting baselines (Swaminathan & Venkitasubramony, 2024; Abolghasemi et al., 2024).

A growing body of literature argues that forecast accuracy should not be treated as the final objective of forecasting studies. Goltsoş et al. (2022) emphasized the existence of a substantial gap between forecasting research and inventory control, where many studies evaluate models using statistical error metrics but do not examine how forecast outputs affect replenishment decisions. This issue is particularly important because a model with lower MAE, MAPE, or RMSE does not always produce better inventory outcomes. A small forecasting error during a high demand period may have greater operational consequences than a larger error during a low demand period (Tadayonrad & Ndiaye, 2023; Babai et al., 2022). Therefore, model evaluation should consider not only statistical accuracy but also operational indicators such as service level, stockout frequency, average on hand inventory, and inventory related costs (Goltsoş et al., 2022; Athanasopoulos et al., 2024; Jebbor et al., 2024).

Inventory policy design requires a clear connection between demand forecasts and replenishment parameters. Safety stock is needed to buffer uncertainty in demand and lead time, while the reorder point determines when replenishment or production should be triggered (Gonçalves et al., 2020; Barros et al., 2021). Recent studies have highlighted that safety stock should ideally be determined not only from historical demand variability but also from forecast error distribution, because the actual uncertainty faced by inventory managers is strongly associated with the difference between forecasted and realized demand (Gonçalves et al., 2020; Lorente Leyva et al., 2024). This perspective is highly relevant for bed linen products, where different size variants may exhibit different levels of volatility and therefore require different inventory buffers (Sodhi et al., 2023; Mendoza, 2025; Ovezmyradov, 2026).

The textile industry provides a strong empirical context for studying the interaction between forecasting and inventory policy. Textile supply chains operate under uncertainty, product variety, and fluctuating market demand, while manufacturers must maintain production efficiency and responsiveness (Kumar et al., 2024; Wang et al., 2024). Recent research in textile and fashion related supply chains has shown the importance of data analytics and

machine learning for improving supply chain planning, disruption prediction, and demand visibility (Wang et al., 2024; Doszyń & Dudek, 2024). Nevertheless, most studies still focus on apparel, fashion retail, or general supply chain forecasting, while empirical studies on home textile products such as bed linen remain relatively limited. This creates an opportunity to examine whether forecasting inventory integration can provide practical benefits in a product category that combines functional usage, size based segmentation, and motif driven consumer preference (Isa et al., 2025; Zhu et al., 2026; Kondo & Vicente, 2023; Abeysooriya et al., 2026).

PT XYZ, a bed linen manufacturer, faces this practical challenge. The company manages seven main size variants of bed linen, with weekly sales and inventory records observed from August 2024 to June 2025. Current production planning is still largely based on managerial experience rather than a standardized forecasting model. This condition may lead to inventory imbalance, particularly when actual demand differs from production assumptions. In this study, the demand behavior of each size variant is first analyzed through exploratory data analysis and demand pattern classification. The forecasting models are then compared using classical time series approaches, and the resulting forecast errors are used as a basis for determining inventory policy parameters (Tadayonrad & Ndiaye, 2023; Kuppulakshmi et al., 2025; Ahmed et al., 2022).

This study contributes to the literature and practice in three ways. First, it provides an empirical analysis of demand forecasting for bed linen products, a home textile category that has received less attention than apparel or general fashion products. Second, it evaluates forecasting models not only through statistical accuracy indicators but also through their implications for inventory policy. Third, it integrates forecast outputs into safety stock and reorder point calculations, thereby translating forecasting results into operational decisions. Through this approach, the study is expected to provide a more structured and data driven framework for reducing overstock and stockout risks, improving service level, and supporting adaptive production planning in textile manufacturing.

Literature Review

Demand Forecasting and Inventory Decisions in Textile Supply Chains

Demand forecasting is a critical component of production and inventory planning, particularly in textile related industries where demand is influenced by product variety, consumer preference, seasonal events, and promotional activities. In the textile and fashion context, demand is often unstable because customers respond not only to functional needs but also to product design, size, color, motif, price, and market trends (Kourentzes et al., 2020; Abolghasemi et al., 2020; Swaminathan & Venkitasubramony, 2024). This condition creates a planning challenge for manufacturers because inaccurate demand forecasts can lead to either excessive inventory or insufficient stock availability.

For home textile products such as bed linen, demand uncertainty is also shaped by size variants, motif preferences, and product replacement cycles. Although bed linen is a functional product, its demand behavior may resemble fashion products because customers often select products based on aesthetic preferences and promotional timing. As a result, production planning based only on managerial intuition may not be sufficient to maintain an efficient balance between stock availability and inventory cost.

From an operational perspective, overestimated demand may cause overproduction, high holding costs, warehouse congestion, and capital tied up in slow moving finished goods. Conversely, underestimated demand may lead to stockouts, lost sales, urgent production decisions, and lower customer satisfaction (Goltsos et al., 2022; Tadayonrad & Ndiaye, 2023).

Therefore, forecasting should not be viewed merely as a statistical activity, but as a decision support process that directly affects production and inventory policies.

In the case of PT XYZ, the company manages seven bed linen size variants using weekly sales and inventory data. The thesis proposal states that the research aims to analyze weekly demand patterns, compare time series forecasting methods, and integrate forecasting results into inventory policies through safety stock and reorder point determination. This makes the study relevant to the broader forecasting inventory integration problem discussed in recent supply chain literature.

Demand Pattern Classification

Demand pattern classification is an important preliminary step before selecting a forecasting model. Different products may exhibit different demand behaviors, even when they belong to the same product category. Some items may have regular and stable demand, while others may show high volatility, irregular demand occurrence, or a combination of both. Therefore, applying a single forecasting model to all stock keeping units may result in poor forecasting and inventory decisions.

In inventory oriented forecasting, demand patterns are commonly classified using the Average Demand Interval (ADI) and the squared Coefficient of Variation (CV^2). ADI measures the average interval between non zero demand occurrences, while CV^2 measures the variability of demand size.

The Average Demand Interval is defined as:

$$ADI_i = \frac{T}{N_i} \quad (1)$$

where T is the total number of observation periods, and N_i is the number of periods with non zero demand for product i .

The squared Coefficient of Variation is calculated as:

$$CV_i^2 = \left(\frac{\sigma_i}{\mu_i} \right)^2 \quad (2)$$

where σ_i is the standard deviation of non zero demand for product i , and μ_i is the mean of non zero demand for product i .

Based on ADI and CV^2 , demand can be classified into four patterns:

$$\begin{cases} \text{Smooth, } ADI < 1.32, CV^2 < 0.49 \\ \text{Erratic, } ADI < 1.32, CV^2 \geq 0.49 \\ \text{Intermittent, } ADI \geq 1.32, CV^2 < 0.49 \\ \text{Lumpy, } ADI \geq 1.32, CV^2 \geq 0.49 \end{cases} \quad (3)$$

This classification is useful because smooth demand can generally be handled using standard time series forecasting models, while erratic, intermittent, or lumpy demand may require more cautious inventory policies. In the bed linen context, popular size variants may show regular but volatile demand, whereas less popular variants may have lower demand frequency. The proposal also states that each SKU will be classified into smooth, erratic, intermittent, or lumpy demand patterns before selecting the appropriate forecasting approach.

Forecast Accuracy Evaluation

Forecasting accuracy is commonly evaluated using error metrics that compare actual demand with forecasted demand. The basic forecast error for period t is defined as:

$$e_t = D_t - \hat{D}_t \quad (4)$$

where D_t is actual demand in period t , and $\hat{D}_t$ is forecasted demand in period t .

The first metric used in this study is Mean Absolute Error (MAE), which measures the average absolute difference between actual and forecasted demand:

$$MAE = \frac{1}{n} \sum_{t=1}^n |D_t - \hat{D}_t| \quad (5)$$

The second metric is Mean Absolute Percentage Error (MAPE), which expresses forecasting error as a percentage of actual demand:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{D_t - \hat{D}_t}{D_t} \right| \quad (6)$$

The third metric is Root Mean Squared Error (RMSE), which gives greater penalty to large forecasting errors:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (D_t - \hat{D}_t)^2} \quad (7)$$

MAE is useful because it is expressed in the same unit as demand, making it easier for managers to interpret. MAPE is useful for comparing forecasting performance across product variants with different demand scales. RMSE is important because large errors may have more serious consequences for inventory decisions, especially when under forecasting occurs during high demand periods (El Jaouhari et al., 2022; Yang et al., 2025; Miguéis et al., 2022).

However, statistical accuracy alone is not sufficient to determine the best forecasting model. A model with the lowest error value may not always produce the best inventory outcome. For example, a model may have a low average error but still cause stockouts if it consistently underestimates demand during peak periods. Therefore, forecasting evaluation should be connected to inventory performance indicators, not only statistical error metrics (Goltsos et al., 2022; Tadayonrad & Ndiaye, 2023).

Forecasting Inventory Integration

The relationship between forecasting and inventory management has become an important topic in recent operations and supply chain studies. Goltsos et al. (2022) describe this issue as the “inventory forecasting gap,” where many forecasting studies focus on improving statistical accuracy but do not examine how forecast outputs influence inventory decisions. In practice, managers do not use forecasts as final results. Forecasts are used as inputs for determining production quantity, replenishment timing, safety stock, and reorder point.

This gap is important because the consequences of forecast errors depend on their direction and timing. Under forecasting may lead to stockouts and lost sales, while over forecasting may increase holding costs and excess inventory. Therefore, forecasting models should be evaluated not only based on MAE, MAPE, and RMSE, but also based on whether they improve inventory related outcomes such as stock availability, service level, fill rate, stockout frequency, and average inventory (Goltsos et al., 2022; Tadayonrad & Ndiaye, 2023; Athanasopoulos et al., 2024).

In this study, forecasting inventory integration is operationalized by using forecast outputs and forecast errors to determine safety stock and reorder point. This approach allows the forecasting model to be directly connected to inventory policy. The proposal explicitly positions this integration as one of the main contributions, where forecasting outputs are not only treated as predicted demand values but are also translated into safety stock and reorder point parameters.

Safety Stock and Reorder Point under Forecast Uncertainty

Safety stock is used to protect the inventory system from uncertainty in demand and lead time. In a forecasting based inventory system, uncertainty can be represented by the variability of forecast errors. Therefore, safety stock can be calculated using the standard deviation of forecast errors:

$$SS = z\sigma_e\sqrt{L} \quad (8)$$

where SS is safety stock, z is the service level factor, σ_e is the standard deviation of forecast error, and L is lead time.

The reorder point determines the inventory position at which replenishment or production should be triggered. It combines expected demand during lead time and safety stock:

$$ROP = \hat{D}_L + SS \quad (9)$$

where ROP is the reorder point, $\hat{D}_L$ is forecasted demand during lead time.

If demand is forecasted on a weekly basis and lead time is expressed in weeks, the reorder point can be written as:

$$ROP = (\hat{D}_{t+1} \times L) + SS \quad (10)$$

where $\hat{D}_{t+1}$ is the forecasted demand for the next period.

This formulation allows inventory policy to reflect both expected future demand and forecasting uncertainty. This is important for bed linen products because each size variant may have a different level of demand volatility. High volume variants may require higher responsiveness to avoid stockouts, while low volume variants may require tighter control to prevent overstock. The proposal also states that safety stock and reorder point are central parameters in the continuous review inventory policy used in this study.

Inventory Performance Indicator: Fill Rate

To evaluate whether the integration of forecasting and inventory policy improves operational performance, inventory indicators are required. One important indicator is fill rate, which measures the proportion of total demand that can be immediately fulfilled from available inventory.

Fill rate can be expressed as:

$$\hat{D}_L \text{ Fill Rate} = \frac{\sum_{t=1}^n \min(D_t, I_t)}{\sum_{t=1}^n D_t} \quad (11)$$

where D_t is actual demand in period t , and I_t is available inventory before demand fulfillment in period t .

A higher fill rate indicates that the company is able to satisfy a larger proportion of customer demand directly from available stock. In the context of forecasting inventory integration, fill rate helps evaluate whether the selected forecasting model contributes to better product availability. This indicator complements statistical forecasting metrics because it reflects the actual operational consequence of forecast based inventory decisions.

Research Gap and Study Positioning

Based on the reviewed literature, several research gaps can be identified. First, many demand forecasting studies still focus mainly on statistical accuracy and do not evaluate whether the selected forecasting model improves inventory performance (Goltsos et al., 2022; Tadayonrad & Ndiaye, 2023; Swaminathan & Venkitasubramony, 2024). Second, most textile and fashion forecasting studies focus on apparel or general fashion products, while home textile products

such as bed linen remain less explored. Third, many advanced forecasting studies require large and rich datasets, whereas many manufacturing firms operate with limited historical data. Fourth, safety stock is often calculated using historical demand variability, although forecast error based safety stock may better represent uncertainty in a forecast driven inventory system (Gonçalves et al., 2020; Barros et al., 2021).

This study addresses these gaps by developing an integrated framework that combines demand pattern classification, classical time series forecasting, forecast accuracy evaluation, and inventory policy formulation. The study evaluates forecasting models using MAE, MAPE, and RMSE, and then connects the forecasting outputs to safety stock, reorder point, and fill rate. Therefore, the proposed framework bridges the gap between forecast accuracy and inventory decision making in the context of bed linen manufacturing.

Methods

Research Design and Case Study Context

This study employs a quantitative case study design to develop and evaluate an integrated demand forecasting and inventory policy framework for PT XYZ, a bed linen manufacturer. The unit of analysis is the stock keeping unit (SKU), represented by seven bed linen size variants: T2 090 B1, T2 100 B1, T2 120 B1, T2 140 B2, T2 160 B2, T2 180 B2, and T2 200 B2. The analysis links two operational decisions: selecting an appropriate weekly demand forecasting model and translating its forecast output into inventory control parameters.

The evaluation framework is designed to assess forecasting models from both statistical and operational perspectives. Statistical forecasting performance is evaluated using MAE, MAPE, and RMSE, while operational performance is assessed through the resulting inventory policy using service level, fill rate, stockout frequency, and average inventory. Thus, the forecasting model is not selected solely according to the lowest statistical error. Its suitability is also determined by whether its forecast output produces an inventory policy that provides adequate demand coverage without unnecessarily increasing inventory levels.

Data Description and Demand Pattern Analysis

The dataset consists of weekly sales and inventory records from August 2024 to June 2025, covering 52 weekly observations for each of the seven SKUs. Data preparation involves checking data completeness, arranging observations chronologically, and separating weekly demand and inventory records for each SKU. Demand characteristics are examined using descriptive statistics, time series plots, stock coverage, and demand pattern classification. Stock coverage is calculated as the ratio of average inventory to average weekly demand and is used as a descriptive indicator of the adequacy of existing inventory relative to demand. Demand patterns are classified using the Average Demand Interval (ADI) and squared Coefficient of Variation (CV^2). The empirical analysis indicates that all seven variants have $ADI = 1$ and $CV^2 < 0.49$, classifying them as smooth demand items. This classification supports the application of classical time series forecasting methods.

Forecasting Model Development and Validation

Six forecasting approaches are compared: Naïve Forecast, Moving Average, Single Exponential Smoothing, Holt's method, Holt Winters, and ARIMA/SARIMA. These methods are selected because the dataset contains only 52 weekly observations and the company requires models that are interpretable and practically implementable.

Model validation uses rolling origin cross validation. The initial training window consists of weeks 1 40 and is used to forecast week 41. The training window is subsequently expanded one week at a time until the final observation, allowing forecasts to be evaluated over multiple

out of sample periods. This procedure reduces dependence on a single train test split and provides a more robust assessment under limited historical data.

Forecast accuracy is evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). MAE measures the average magnitude of forecasting errors in the original demand unit, MAPE provides a scale independent percentage measure, and RMSE gives greater weight to larger forecasting errors. Lower values indicate better forecasting accuracy for all three metrics.

The Diebold Mariano (DM) test is additionally applied to determine whether differences in predictive accuracy between competing models are statistically significant. When the difference between two models is not statistically significant, model selection considers practical simplicity and interpretability rather than treating a small numerical difference in forecast error as evidence of superior performance.

Inventory Policy Integration and Performance Evaluation

The selected forecasting model for each SKU is integrated into inventory policy through safety stock and reorder point determination. The next period forecast is used to estimate demand during lead time, while the standard deviation of forecast errors is used to represent demand uncertainty. Safety stock and reorder point are calculated as follows:

$$SS_i = z\sigma_{e,i}\sqrt{L_i} \quad (12)$$

$$ROP_i = (\hat{D}_{i,t+1} \times L_i) + SS_i \quad (13)$$

where SS_i is safety stock, z is the service level factor, $\sigma_{e,i}$ is the standard deviation of forecast error, L_i is lead time, and ROP_i is the reorder point for product i . Inventory performance is evaluated using fill rate, stockout frequency, and average inventory. The final model is selected based on the balance between forecast accuracy and inventory performance. Therefore, the best model is not necessarily the one with the lowest statistical error, but the one that provides the most appropriate inventory decision support for each SKU.

Inventory Performance Evaluation and Model Selection

Inventory performance is evaluated using four measurable indicators: service level, fill rate, stockout frequency, and average inventory. Service level represents the target probability of satisfying demand without a stockout, while fill rate measures the proportion of demand fulfilled directly from available inventory. Stockout frequency represents the number of periods in which available inventory is insufficient to satisfy demand. Average inventory represents the average quantity of finished goods held during the evaluation period.

These indicators are used to assess whether a forecasting model produces operationally appropriate inventory decisions. A model that generates lower forecasting errors but substantially higher stockout frequency or excessive inventory is not automatically considered superior.

Model selection follows a predefined decision rule. First, forecasting models are compared using MAE, MAPE, and RMSE. Second, statistically indistinguishable models based on the Diebold Mariano test are treated as having comparable predictive performance. Third, the inventory policies generated by the competing models are evaluated under the same lead time and service level assumptions. Among models that satisfy the target service level requirement, preference is given to the model producing lower stockout frequency and lower average inventory. When operational performance is comparable, the simpler and more interpretable forecasting model is preferred. This decision rule ensures that model selection is based on both predictive accuracy and measurable inventory consequences. The evaluation therefore distinguishes between two levels of performance. Forecasting accuracy determines how well

a model predicts future demand, whereas inventory performance determines whether those predictions can be translated into appropriate replenishment decisions. The final model for each SKU is selected only after both dimensions have been considered.

Comparative Inventory Evaluation

To demonstrate the operational consequences of forecasting model selection, the inventory policy generated by each competing forecasting model is evaluated using the same historical validation framework. Each model produces its own forecast, forecast error distribution, safety stock, and reorder point, while lead time and target service level are held constant across models. This ensures that differences in inventory performance are attributable primarily to the forecasting model rather than differences in inventory policy assumptions. The comparison focuses on whether each forecasting model can achieve the required service level target while minimizing unnecessary inventory exposure. The preferred model is therefore the model that provides an appropriate balance between demand coverage and inventory efficiency rather than simply the model with the smallest forecasting error.

Because the available case data do not provide a fully documented historical inventory policy based on the company's previous managerial decisions, the analysis does not claim a causal improvement over the company's existing practice. Instead, the study evaluates the relative operational performance of inventory policies generated by the competing forecasting models under standardized assumptions. This approach provides objective evidence for selecting a forecasting model while avoiding unsupported claims regarding the effectiveness of the proposed framework relative to an undocumented baseline.

Analytical Framework

The overall analytical procedure consists of five sequential stages. First, weekly sales and inventory data are prepared and analyzed descriptively. Second, each SKU is classified according to ADI and CV^2 . Third, the six forecasting approaches are evaluated using rolling origin cross validation and statistical accuracy measures. Fourth, forecast outputs and forecast errors are translated into safety stock and reorder point parameters under predefined service level and lead time assumptions. Fifth, the resulting inventory policies are compared using service level, fill rate, stockout frequency, and average inventory. This integrated procedure establishes an objective link between forecasting performance and inventory decisions. The final forecasting model for each SKU is therefore determined not only by statistical accuracy but also by its measurable ability to support an inventory policy that maintains adequate product availability while limiting unnecessary finished goods inventory.

Results and Discussion

Demand and Inventory Characteristics

The analysis of 52 weeks of weekly demand data shows that all seven bed linen variants are classified as smooth demand, with $ADI = 1.00$ and $CV^2 < 0.49$. Although this classification indicates that demand occurs regularly across all observation periods, it does not imply that the seven SKUs have identical demand behavior. Substantial differences remain in demand volume, variability, and short term movement. T2 120 B1 records the highest mean weekly demand at 554.73 units, while T2 200 B2 has the lowest mean weekly demand at 228.21 units. The standard deviation also varies considerably, ranging from 78.50 units for T2 140 B2 to 269.64 units for T2 120 B1. These differences provide an important explanation for why a single forecasting model does not necessarily perform equally well across all SKUs.

The forecasting evaluation confirms that no single model dominates across all products. Holt Winters(4) produces the best performance for T2 090 B1, T2 100 B1, T2 140 B2, T2 160 B2, and T2 180 B2, whereas the Naïve Forecast performs best for T2 120 B1 and ARIMA(0,1,2)

performs best for T2 200 B2. The results indicate that demand regularity alone is insufficient to determine forecasting model suitability. Instead, model performance is influenced by the characteristics of the individual demand series. The relatively strong performance of Holt Winters(4) for five SKUs suggests that these products contain short term level and recurring movement that can be captured through exponential smoothing components. This interpretation is consistent with the fact that these SKUs exhibit regular weekly demand but differ in their magnitude and variability. Holt Winters therefore provides a flexible representation of repeated short term movements without requiring a long historical series.

The Naïve Forecast performs best for T2 120 B1 despite this SKU having the highest average weekly demand and one of the largest demand standard deviations. This result suggests that the most recent observation provides a useful representation of its immediate future demand, making a more complex model unnecessary for short horizon prediction. The result also demonstrates that high demand volume does not automatically imply that a more sophisticated forecasting model will perform better.

For T2 200 B2, ARIMA(0,1,2) provides the lowest MAE and RMSE among the evaluated models. The use of an integrated ARIMA specification indicates that the series benefits from differencing and autoregressive moving average error structure. However, this interpretation should be treated cautiously because the study contains only 52 weekly observations. The model's selection reflects its relative predictive performance within the observed dataset rather than evidence that ARIMA is generally superior for low volume products.

The Diebold Mariano results further show that differences between the best and second best forecasting models are not statistically significant for all variants. Consequently, the numerical superiority of a model should not automatically be interpreted as evidence of substantial predictive superiority. When competing models provide statistically comparable forecasts, model simplicity, interpretability, and implementation requirements become relevant considerations for PT XYZ.

Table 1. Descriptive statistics of weekly demand and inventory

Product Variant	Total Sales	Mean Weekly Sales	Std. Deviation	Min	Max	Average Stock	Stock Coverage
T2 090 B1	23,765	457.02	177.21	119	918	522.77	1.14
T2 100 B1	15,083	290.06	133.64	29	611	706.77	2.44
T2 120 B1	28,846	554.73	269.64	96	1,441	599.28	1.08
T2 140 B2	13,208	254.00	78.50	116	468	1,595.63	6.28
T2 160 B2	24,890	478.65	196.87	202	1,303	848.35	1.77
T2 180 B2	25,915	498.37	215.95	142	1,252	923.79	1.85
T2 200 B2	11,867	228.21	113.83	33	588	999.83	4.38

The sales contribution pattern is illustrated in Fig. 1. The figure shows that T2 120 B1, T2 180 B2, T2 160 B2, and T2 090 B1 dominate overall demand. These four variants account for the majority of sales and should therefore receive stronger attention in forecasting and inventory planning.

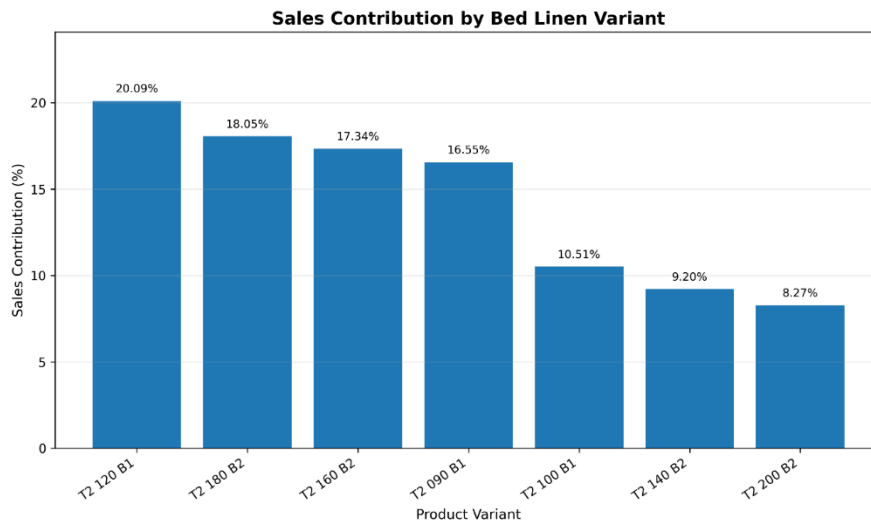


Figure 1. Sales contribution of each bed linen size variant during the 52 week observation period.

In contrast, the stock coverage analysis in Fig. 2 shows that inventory allocation is not proportional to demand contribution. T2 120 B1 has the highest sales contribution but only 1.08 weeks of stock coverage. Similarly, T2 090 B1 has only 1.14 weeks of stock coverage. These conditions indicate potential stockout risk. On the other hand, T2 140 B2 and T2 200 B2 have lower demand contributions but much higher stock coverage, reaching 6.28 weeks and 4.38 weeks, respectively. This suggests potential overstock. This finding confirms that PT XYZ does not only face a forecasting problem, but also an inventory allocation problem. High demand variants tend to be underprotected, while lower demand variants hold excessive stock.

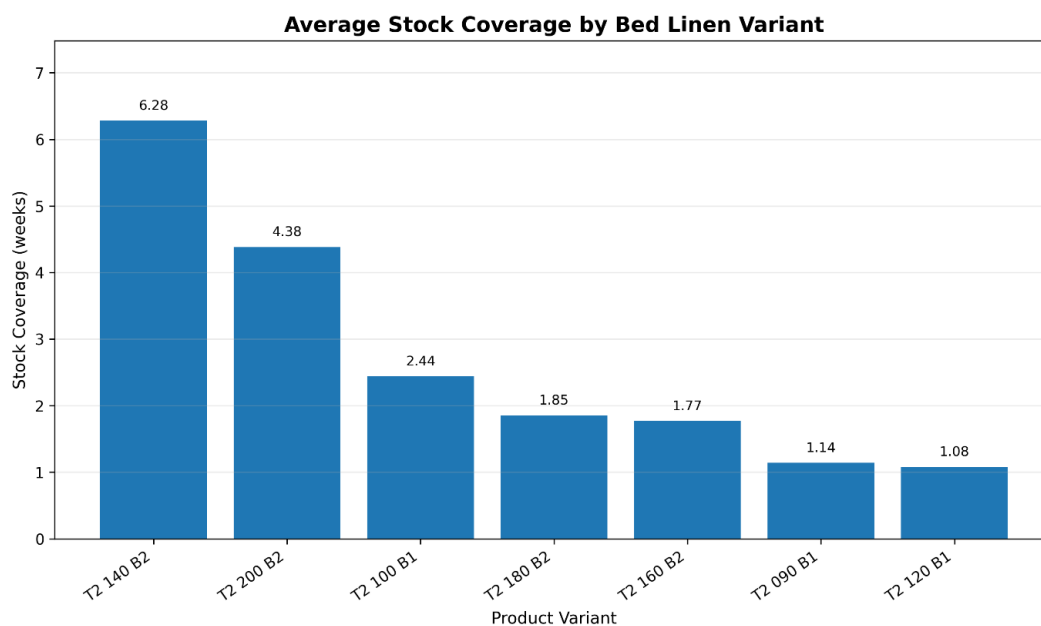


Figure 2. Average stock coverage of each bed linen size variant.

Demand Pattern and Stationarity Analysis

Demand pattern classification was conducted using ADI and CV^2 . The results show that all seven variants have $ADI = 1.00$ and $CV^2 < 0.49$, meaning that all variants are classified as smooth demand.

Table 2. Demand pattern classification and stationarity test

Product Variant	Selected Model	MAE	MAPE (%)	RMSE
T2 090 B1	Holt Winters(4)	98.01	16.90	120.06
T2 100 B1	Holt Winters(4)	93.94	26.55	124.46
T2 120 B1	Naïve	113.58	21.64	134.72
T2 140 B2	Holt Winters(4)	66.53	25.48	80.28
T2 160 B2	Holt Winters(4)	88.90	23.84	109.76
T2 180 B2	Holt Winters(4)	123.91	27.85	152.24
T2 200 B2	ARIMA(0,1,2)	48.91	29.67	60.22

The results show that no single model dominates all variants. Holt Winters(4) performs best for five variants, while Naïve Forecast performs best for T2 120 B1, and ARIMA(0,1,2) performs best for T2 200 B2. This confirms that forecasting should be performed at the SKU level rather than using a single model for all products. The relatively strong performance of Holt Winters indicates that several bed linen variants may contain short term repeated fluctuations. Meanwhile, the performance of Naïve Forecast for T2 120 B1 suggests that its short term demand movement is strongly influenced by the most recent observation. For T2 200 B2, ARIMA(0,1,2) is consistent with its non stationary demand behavior. The Diebold Mariano test indicates that the differences between the best and second best models are not statistically significant for all variants. This means that when two models produce similar accuracy, PT XYZ may prioritize simpler and more interpretable models for practical implementation.

Forecasting Inventory Policy Integration

The selected forecasting model for each SKU was then integrated into inventory policy. The model provides two key inputs: the next period forecast and the forecast error standard deviation. The forecast is used to estimate demand during lead time, while the forecast error standard deviation is used to calculate safety stock. The main inventory scenario uses a 95% service level, corresponding to $z=1.645$, and assumes a one week lead time.

Table 4. Forecast based inventory policy parameters at 95% service level

Product Variant	Selected Model	Next period Forecast	Forecast Error SD	Safety Stock	Reorder Point
T2 090 B1	Holt Winters(4)	462.83	124.63	205.02	667.85
T2 100 B1	Holt Winters(4)	322.74	126.96	208.86	531.59
T2 120 B1	Naïve	526.00	136.87	225.16	751.16
T2 140 B2	Holt Winters(4)	244.87	83.25	136.95	381.82
T2 160 B2	Holt Winters(4)	334.45	114.47	188.31	522.76
T2 180 B2	Holt Winters(4)	294.75	158.99	261.54	556.29
T2 200 B2	ARIMA(0,1,2)	176.37	62.85	103.38	279.75

The results show that safety stock requirements differ across product variants. T2 180 B2 has the highest safety stock requirement because it has the largest forecast error standard deviation. T2 120 B1 also requires relatively high safety stock due to its large demand volume and low stock coverage. This confirms that safety stock should not be assigned uniformly across all products. A forecast error based approach allows the company to align inventory buffers with the actual uncertainty of each SKU.

To examine the effect of different service levels, three scenarios were evaluated: 90%, 95%, and 97.5%. The 90% scenario results in lower safety stock and lower reorder points, while the 97.5% scenario provides stronger availability protection but requires higher inventory investment. For high volume products such as T2 120 B1, the 95% scenario is more appropriate because stockout may directly reduce sales. For products with high stock coverage such as T2 140 B2 and T2 200 B2, a lower service level may be sufficient to prevent further overstock. The existing inventory adequacy proxy also confirms the imbalance. T2 120 B1 shows the highest stockout indication, while T2 140 B2 and T2 200 B2 show no stockout indication but have excessive average stock. Therefore, the proposed framework helps distinguish between products that need stronger stock protection and products that require tighter replenishment control.

Managerial Implications

The results provide several practical implications for PT XYZ. First, demand planning should be conducted separately for each size variant. Although all products are classified as smooth demand, their demand volume, stationarity, forecast error, and stock coverage differ substantially. Second, high volume products with low stock coverage should become priority items in inventory monitoring. T2 120 B1 is the most critical variant because it has the highest sales contribution and low stock coverage. For this product, reorder point should be used as an early warning signal to trigger production or replenishment before stockout occurs. Third, lower demand products with high stock coverage require inventory rationalization. T2 140 B2 and T2 200 B2 should not be replenished automatically unless their inventory position falls below the calculated reorder point. This policy can help reduce unnecessary inventory accumulation and improve cash flow efficiency. Fourth, PT XYZ does not need to begin with highly complex forecasting systems. Since the Diebold Mariano test shows no statistically significant difference between the best and second best models, simpler models may be preferable when their accuracy is comparable. This is important for a company transitioning from intuition based planning to data driven inventory control. Overall, the findings demonstrate that forecast accuracy alone is not sufficient. The real value of forecasting lies in its ability to support inventory decisions. By converting forecasting outputs and forecast errors into safety stock and reorder point parameters, PT XYZ can improve stock availability for high demand products while reducing excessive inventory for slower moving variants.

Forecast Accuracy and Operational Relevance

The selected models produce MAE values ranging from 48.91 to 123.91 units, MAPE values from 16.90% to 29.67%, and RMSE values from 60.22 to 152.24 units across the seven SKUs. T2 200 B2 records the lowest MAE and RMSE, while T2 090 B1 records the lowest MAPE. In contrast, T2 180 B2 has the highest MAE and RMSE, indicating greater absolute forecasting uncertainty for this SKU.

These values should be interpreted as relative performance measures within the case rather than as universally acceptable forecasting thresholds. The available data do not establish an industry specific accuracy benchmark for bed linen manufacturing, and therefore the study does not claim that a particular MAPE or MAE value represents an absolute standard of forecasting quality. Instead, the metrics are used to compare alternative models under identical validation conditions. This distinction is important because forecasting acceptability depends on the operational consequences of forecast errors, including demand volume, inventory exposure, lead time, and required service level.

The operational relevance of the forecasting results is therefore assessed through their integration with inventory policy. A forecasting model with a lower statistical error is operationally useful only when its forecast and error distribution can support an appropriate safety stock and reorder point. This approach addresses the forecasting inventory gap

identified in previous research, where forecasting models are frequently evaluated independently from the inventory decisions they support.

Forecasting Inventory Integration

The selected forecasting models generate different inventory requirements because forecast levels and forecast error variability differ across SKUs. Under the 95% service level scenario and one week lead time, safety stock ranges from 103.38 units for T2 200 B2 to 261.54 units for T2 180 B2. T2 180 B2 requires the highest safety stock because it has the largest forecast error standard deviation at 158.99 units. T2 120 B1 also requires a relatively high safety stock of 225.16 units, reflecting its combination of high demand volume and substantial forecast uncertainty. The resulting reorder points range from 279.75 units for T2 200 B2 to 751.16 units for T2 120 B1. These differences demonstrate that inventory parameters should be determined at the SKU level rather than uniformly across all bed linen variants. The integration translates forecast uncertainty into explicit inventory buffers, allowing products with greater uncertainty to receive larger safety stocks while avoiding the assumption that every SKU requires the same protection level.

The comparison with existing stock coverage further demonstrates the operational relevance of the framework. T2 120 B1 has the highest sales volume but only 1.08 weeks of stock coverage, while T2 090 B1 has 1.14 weeks of coverage. Conversely, T2 140 B2 and T2 200 B2 have substantially higher stock coverage of 6.28 and 4.38 weeks, respectively. The results therefore indicate an imbalance between demand contribution and inventory allocation: high demand products have relatively limited coverage, whereas lower demand products carry considerably more inventory. However, the results should not be interpreted as demonstrating a quantified reduction in stockout frequency, holding cost, or excess inventory relative to the company's current policy. The available dataset does not provide a sufficiently documented historical baseline policy against which such improvements can be causally measured. Instead, the present analysis demonstrates the inventory implications of the proposed forecasting models and identifies which SKUs require stronger stock protection or tighter inventory control.

Service Level Sensitivity

The service level analysis evaluates 90%, 95%, and 97.5% scenarios. Increasing the service level increases the safety stock and consequently raises the reorder point, while a lower service level reduces inventory requirements but provides less protection against stockouts. This relationship confirms the expected trade off between inventory investment and product availability. The 95% scenario provides an intermediate reference point between inventory protection and inventory investment. However, the results do not provide sufficient cost information to establish that 95% is economically optimal for every SKU. In particular, the study does not contain complete holding costs, stockout costs, lost sales costs, or production adjustment costs. Therefore, recommendations regarding service level should be interpreted as operational scenarios rather than definitive cost optimal policies.

Overall Interpretation

Overall, the findings demonstrate that the relationship between demand characteristics, forecasting performance, and inventory policy is SKU specific. Although all seven variants are classified as smooth demand, differences in demand magnitude, variability, and short term behavior result in different forecasting models achieving the best relative performance. Holt Winters(4) is preferred for five SKUs, Naïve Forecast for T2 120 B1, and ARIMA(0,1,2) for T2 200 B2. The main practical contribution is therefore not the identification of one universally superior forecasting method, but the development of a SKU specific decision framework in which forecasting accuracy is translated into safety stock and reorder point

requirements. The results show that T2 120 B1 requires particular attention because of its high demand contribution and low stock coverage, whereas T2 140 B2 and T2 200 B2 require tighter inventory control because of their relatively high stock coverage.

Future evaluation should extend this framework by incorporating actual inventory holding costs, stockout or lost sales costs, production adjustment costs, and historical replenishment decisions. Such information would enable a formal cost benefit analysis and determine whether the 90%, 95%, or 97.5% service level scenario provides the economically optimal balance between inventory investment and customer availability for each SKU.

Conclusion

This study developed an integrated demand forecasting and inventory policy framework for bed linen products at PT XYZ using 52 weeks of sales and inventory data from seven size variants. The results show that all variants are classified as smooth demand, indicating that demand occurs regularly in every observation period. However, the products differ substantially in sales contribution, demand variability, stationarity, stock coverage, and forecast error. This confirms that a single forecasting and inventory policy cannot be applied uniformly across all variants. The descriptive analysis reveals an inventory imbalance. High demand products such as T2 120 B1 and T2 090 B1 have relatively low stock coverage, indicating potential stockout risk. In contrast, lower demand variants such as T2 140 B2 and T2 200 B2 show high stock coverage, suggesting potential overstock. These findings indicate that PT XYZ faces not only a demand forecasting problem but also an inventory allocation problem.

The forecasting evaluation shows that no single model dominates all products. Holt Winters(4) performs best for most variants, while Naïve Forecast is more suitable for T2 120 B1 and ARIMA(0,1,2) performs best for T2 200 B2. This result highlights the importance of SKU specific forecasting. Since the Diebold Mariano test shows no significant differences between the best and second best models, simpler models may be preferable when their accuracy is comparable. The main contribution of this study lies in integrating forecasting outputs with inventory policy. Forecast errors were used to calculate safety stock, while forecasted demand was used to determine reorder points. This approach enables PT XYZ to align inventory buffers with the uncertainty of each product variant. Overall, the proposed framework supports a transition from intuition based planning to data driven inventory control. Future research may incorporate longer historical data, actual holding and stockout costs, promotional variables, motif variation, and customer level fulfillment data to improve model robustness and practical applicability.

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