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Improving Demand Forecasting Accuracy for Pharmaceutical Injection Products Using Time-Series Methods: Evidence from an Indonesian Pharmaceutical Manufacturer

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Abstract: *The pharmaceutical industry requires an accurate demand forecasting system to support production planning, inventory control, and service level improvement, especially for injection products that have critical and fluctuating demand characteristics. This study aims to evaluate the most suitable time-series forecasting method for predicting demand for Injection Product X at an Indonesian pharmaceutical company and to provide a basis for improving the demand-planning process. The research uses a quantitative case study approach, drawing on historical monthly demand data from 2020 to 2024. Three time series methods are compared: Double Moving Average, Double Exponential Smoothing, and the Winter Method (Holt-Winters). Accuracy evaluation is conducted using Mean Absolute Percentage Error, Mean Absolute Deviation, and Mean Squared Error. The best method is then validated using moving range and used to forecast demand for the next 12 periods. The research results indicate that the conventional forecasting method based on simple averaging yields a high error rate, with a Mean Absolute Percentage Error of 56.211%, and is therefore categorized as inaccurate. After comparing methods, Double Exponential Smoothing yielded a Mean Absolute Percentage Error of 25.825%, Double Moving Average was 23.477%, and the Winter Method was 20%. The Winter Method became the best method because it captured the trend and seasonal components in the demand data for Injection Product X. Validation using the moving range showed that all error values were within control limits, indicating that the model is stable and suitable for use. The forecast results for the next 12 periods provide a quantitative basis for the company to prepare production plans, procure raw materials, control inventory, and anticipate the risks of overstocking and stockouts. This study confirms that selecting a forecasting method appropriate to the characteristics of the data pattern can improve forecast accuracy and strengthen the demand planning process in the pharmaceutical industry. The main contribution of this study lies in applying comparative time-series methods at the level of individual pharmaceutical products and in strengthening data-based forecasting SOP recommendations.*

Keywords—*demand forecasting*; *time series forecasting*; Winter Method; pharmaceutical inventory; production planning.

1. INTRODUCTION

The pharmaceutical industry plays a strategic role in the healthcare system by developing, producing, and distributing medicines to meet the community's medical needs. In this context, pharmaceutical companies are not only required to produce effective products but also to ensure that each product meets quality, safety, and efficacy standards in accordance with applicable regulations. These challenges become increasingly complex with injectable products, especially anti-inflammatory and anti-allergy injections, because they are often needed for medical conditions that require a quick response. The characteristic of injectable medicines that can provide rapid therapeutic effects makes their availability very important, especially in emergency situations. Therefore, pharmaceutical supply chain management must be directed not only at cost efficiency but also at maintaining product availability on time, in the right quantity, and in line with market needs. In this context, demand forecasting is an important tool for supporting production planning, inventory control, and service-level improvement in the pharmaceutical industry. Initial reports indicate that demand forecasting helps pharmaceutical companies plan production, manage inventories, and ensure medicine availability in the market amid frequent demand fluctuations.

Conceptually, forecasting provides an overview of the conditions a company will face in the future and can serve as a basis for determining strategic steps to meet consumer demand. Although forecast results are not always entirely accurate because the future contains elements of uncertainty, selecting an appropriate method can reduce forecasting error [1-5]. From an operational perspective, forecasting also serves as a basis for decision-making, given the time lag between decision and implementation, and improves the effectiveness of production and sales plans [1;3;6-7]. Therefore, forecasting is not merely a technical activity to estimate demand figures but part of a decision-making system that influences production, raw material purchasing, warehouse capacity, distribution, and the fulfillment of customer needs. In the pharmaceutical industry, the accuracy of forecasting becomes increasingly important because products have shelf-life limits, strict quality regulations, and more critical health-service implications than general manufacturing products.

The main issue faced in pharmaceutical product demand planning is the high variability in demand. Medication demand can change due to seasonal factors, increases in certain disease cases, outbreaks, changes in market behavior, tender patterns, distribution policies, or shifts in healthcare facility needs. For example, demand for anti-inflammatory and anti-allergy injection products may increase during periods when cases of allergies or inflammatory conditions rise. These fluctuations pose challenges for companies in determining the optimal production quantity. If a company produces too much, the risk of overstock increases, which can lead to high storage costs and potential product expiration. Conversely, if a company produces too little, the risk of stockouts increases, potentially leading to lost sales opportunities and disruptions in meeting patient needs. In the initial draft, historical demand data for Product X from 2020 to 2024 show fluctuating patterns, making inventory management challenging and requiring more accurate forecasting methods.

The issue becomes even more apparent when the company still uses a conventional forecasting approach based on simple averages. Based on direct observation with the Inventory and Control Logistics Manager, the forecasting process in place results in a high error rate. Verification of previous forecasting results shows a Mean Absolute Deviation value of 64,440.388, a Mean Squared Error of 5,200,385,080.091, and a Mean Absolute Percentage Error of 56.211%. The MAPE value is categorized as inaccurate because it exceeds 50%, while the MAPE classification states that values below 10% indicate highly accurate forecasts, 10%–20% are good, 20%–50% are acceptable or reasonable, and over 50% are poor or inaccurate [8-10]. High forecasting errors can lead to overstocking or understocking during certain periods, ultimately resulting in higher storage costs, lost sales opportunities, and reduced company profitability. Another identified obstacle is the lack of human resources with specialized forecasting skills, so simple methods are still used in operational practice.

A common solution to this issue is to apply a more suitable quantitative forecasting method that aligns with the characteristics of the historical data. Forecasting can generally be divided into qualitative and quantitative methods. Qualitative methods are used when past data is unavailable or difficult to obtain, but tend to be subjective because they rely heavily on human judgment [1;3;6;7]. Conversely, quantitative methods are employed when past data are available, are quantifiable, and exhibit patterns relevant to projecting future needs. Quantitative models include regression, econometric, and time series models [1;3;6;7]. Quantitative methods are formal procedures that use mathematical models, based on historical data, to project future needs [11;12]. Therefore, for Product X demand, which has monthly historical data over several years, a time-series-based quantitative approach is a more appropriate methodological choice than a simple average.

Specifically, the time series method is relevant because demand data is organized in time order and observed periodically. This method allows researchers to recognize patterns, trends, fluctuations, and seasonal components in the data, enabling more systematic forecasting of future values [1;8;13]. In the forecasting literature, some commonly used time series methods include Single Moving Average, Double Moving Average, Single Exponential Smoothing, Double Exponential Smoothing, and the Winter (Holt-Winters) Method. Single Moving Average works by averaging the most recent actual data points to predict the next demand and is adaptive to new data [1;14]. The Double Moving Average is designed to minimize errors in trended data by calculating a moving average of moving averages, making it more responsive to changes in data patterns [1;14]. Meanwhile, Single Exponential Smoothing is used to smooth historical data by assigning specific weights to previous data [1;4-5], whereas Double Exponential Smoothing is more suitable for data with trend patterns because it performs smoothing twice [1;14].

The Winter (Holt-Winters) method is relevant for data with trends and seasonality. The Winter method is a time series forecasting technique suitable for data with clear trends and seasonal patterns [1;6;8]. This method considers three main components: level, trend, and seasonality, making it theoretically better suited to capturing demand dynamics that not only increase or decrease but also recur at specific periods. Previous literature shows that time series methods have been widely used in various contexts, such as comparing Moving Average, Single Exponential Smoothing, and Double Exponential Smoothing for LPG cylinder demand, where Double Exponential Smoothing was found to be the best method; inflation forecasting post-election using Double Exponential Smoothing; material requirement forecasting with Moving Average and Exponential Smoothing; and the application of Holt-Winters on international tourist numbers and monthly gold prices. However, studies that specifically compare time-series methods for injectable pharmaceutical products at the individual product or SKU level and link the results to improvements in demand-planning procedures remain relatively limited. This gap is important because the demand for pharmaceutical products has critical characteristics influenced by market uncertainty and public health, with direct implications for healthcare services and inventory costs.

Based on the background described above, this study aims to determine a more accurate demand forecasting method for Injection Product X in 2025 and to develop a basis for improving the company's forecasting procedures. The novelty of this study lies in the application of comparative methods—Double Moving Average, Double Exponential Smoothing, and Winter Method—to demand data for pharmaceutical injection products at the individual product level, with accuracy evaluation using MAPE, MAD, and MSE, and validation using moving range. The methodological justification of this study is based on the hypothesis that time series methods that account for historical patterns, especially trends and seasonality, will achieve greater accuracy than the simple averaging method traditionally used. The scope of the study is limited to the demand for Injection Product X at PT Phapros Tbk, using historical demand data from 2020 to 2024, with a focus on selecting the best forecasting method and developing recommendations for production planning and inventory control.

2. METHODOLOGY

2.1 Research Design

This research uses a quantitative case study design, employing a comparative approach across several time-series forecasting methods. This design was chosen because the study's main goal is not only to describe historical demand patterns but also to evaluate the most accurate forecasting methods to support production decision-making and inventory control in the pharmaceutical industry. Methodologically, this study places historical demand data as the primary basis for building the forecasting model. This approach aligns with the characteristics of quantitative forecasting, which uses historical data to project future needs. In the literature, quantitative methods are used when historical data are available and exhibit predictable patterns that can serve as a basis for prediction, whereas qualitative methods rely more on human judgment when past data are unavailable or insufficient [1;3;6;7;11;12].

The case study design was chosen because the research focuses on a specific object, namely Injection Product X at PT Phapros Tbk. This product's demand characteristics fluctuate and directly impact decisions related to production, inventory, and customer demand fulfillment. Based on the initial problem, the company is still using the simple average method for forecasting, which results in significant errors. Verification of the initial method showed a Mean Absolute Deviation of 64,440.388, a Mean Squared Error of 5,200,385,080.091, and a Mean Absolute Percentage Error of 56.21%. The MAPE value indicates that the method used is inaccurate and could lead to overstocking or understocking during certain periods. This condition underscores the need for a more systematic, data-driven forecasting method that aligns with historical demand patterns.

2.2 Research Object and Scope

The research objective is the demand for Product Injection X in units. The study was conducted at PT Phapros Tbk, specifically to address demand planning needs across the logistics, inventory, and production control departments. In the initial document, the scope of the research was limited to using demand data for Product Injection X, processing time-series data, and validating forecast results using the moving range method. The research was conducted during the internship period from January 6 to February 6, 2025, at PT Phapros Tbk's Semarang Factory Unit. These boundaries are important for keeping the analysis focused on the main issue: selecting the best forecasting method for a pharmaceutical product with a specific historical demand pattern.

In the context of scientific articles, restricting objects to a single product or SKU can be viewed as a methodological strategy to obtain a more in-depth analysis. Pharmaceutical product demand at the SKU level often varies across products, so aggregating data at the product group level can conceal important demand variations. Therefore, analysis at the level of Injection Product X allows researchers to evaluate the performance of forecasting methods more specifically and operationally. The scope of the research does not include causal analysis of external factors such as epidemics, promotions, tender policies, or changes in distribution channels. The main focus of this study is demand forecasting based on historical demand patterns using a time series approach.

2.3 Data Source and Data Collection

The data used in the research consists of primary and secondary data. Primary data was obtained through direct observation and interviews with the company, specifically the Inventory and Control Logistics Manager and staff involved in the demand planning process. The interviews were conducted to understand the actual conditions of the forecasting process, the issues that occur, resource limitations, and the company's needs for a more structured forecasting procedure. Secondary data includes historical demand or sales data for Injection Product X, relevant company documents, and scientific literature used to select methods and evaluate forecast accuracy. In the initial document, data collection techniques include interviews and literature review, while data sources comprise primary data from observations and secondary data from the inventory and control logistics department of PT Phapros Tbk.

The historical data used includes the actual demand for Injection Product X from 2020 to 2024. The data is organized as a monthly time series, making it suitable for analysis using time-series methods. Before modeling is performed, the data is plotted to observe general trends, fluctuations, patterns, and potential seasonal effects. This visual exploration stage is important because the choice of forecasting method must be adjusted to the characteristics of the data. If the data has no trend, methods such as Single Moving Average or Single Exponential Smoothing can be used. If the data has a trend, Double Moving Average or Double Exponential Smoothing are more relevant. Meanwhile, if the data show seasonal patterns, the Winter or Holt-Winters methods are more appropriate because they account for level, trend, and seasonal components.

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2.4 Forecasting Method Selection

The selection of forecasting methods in this study is based on the characteristics of the historical data pattern. The demand plot for Injection Product X shows fluctuations and a trend tendency, so the methods used are Double Moving Average, Double Exponential Smoothing, and the Winter Method. These three methods were chosen because each has different capabilities in capturing data patterns. Double Moving Average is a method that calculates the average of the moving averages. This method is relevant for trended data because it can reduce forecasting errors compared to single-moving-average methods and is more responsive to changes in data patterns [1;14].

Double Exponential Smoothing is used because this method is designed for data with trend patterns through a process of double smoothing. This method adjusts the discrepancy between historical data and forecast results by adding the second smoothing value to the first. The literature states that Double Exponential Smoothing is suitable for data with a trend tendency and is useful for addressing trend changes and fluctuations by giving greater weight to the most recent data [1;14]. Meanwhile, the Winter Method, or Holt-Winters, is used because it is appropriate for data with clear trends and seasonal patterns. This method considers three main components, namely level, trend, and seasonality, making it more capable of capturing the recurring demand dynamics over time [1;6;8].

The criteria for selecting a method are based not only on theoretical suitability but also on empirical performance measured by error metrics. Therefore, this study does not assume from the outset that one method is necessarily better, but compares all methods based on the error values they produce. This comparative approach is important to ensure that the chosen method is truly supported by quantitative evidence.

2.5 Forecasting Procedure

The research procedure is carried out in stages. First, the research problem is identified based on the company's actual conditions, namely the high error rate of conventional forecasting methods and the lack of a structured operational forecasting standard. Second, the scope of the research is determined by selecting Injection Product X as the study object and demand data from 2020 to 2024 as the basis for analysis. Third, historical data is collected and visualized using time-series plots to identify demand patterns. Fourth, the forecasting methods are chosen based on the characteristics of the data patterns. Fifth, forecasts are made using Double Moving Average, Double Exponential Smoothing, and Winter's Method. Sixth, the results of each method are evaluated using MAPE, MAD, and MSE. Seventh, the method with the smallest error is selected as the best. Eighth, the selected method is validated using the moving range. Ninth, the validated method is used to forecast demand for the next 12 periods.

These stages align with the research flow in the initial document, which includes problem identification, scope determination, literature review, field study, data plotting, forecasting method selection, error calculation for each method, selection of the best method, validation, analysis, and preparation of conclusions and recommendations.

2.6 Forecast Accuracy Measurement

Forecast accuracy evaluation is conducted using three main metrics: Mean Absolute Percentage Error, Mean Absolute Deviation, and Mean Squared Error. MAPE measures the average percentage of absolute errors relative to actual values. This metric is important because it provides a percentage interpretation, making it easy to compare the performance of different methods. The smaller the MAPE value, the better the forecasting model's performance. In the initial document, the classification of MAPE refers to [8;9;10], which states that an MAPE of less than 10% indicates an excellent model, 10%–20% is good, 20%–50% is fair, and more than 50% is poor.

MAD measures the average absolute error of forecasts in the same units as the actual data. This metric indicates how large the average deviation of forecast results is from actual demand. Meanwhile, MSE calculates the average squared error and is useful for assigning greater weight to extreme errors. The use of these three metrics provides a more comprehensive evaluation because MAPE emphasizes relative accuracy, MAD emphasizes absolute deviations, and MSE emphasizes the magnitude of squared errors. Literature in the initial document mentions that MAPE shows the size of forecast errors relative to actual values, MAD measures errors in the same units as the original series, while MSE is used to observe the magnitude of squared errors and potential bias in the forecasting method [1;4;5].

2.7 Forecast Validation

Model validation is conducted to ensure that the selected method not only has the smallest error but also produces a stable error pattern. In this study, validation was performed using the moving range method. This approach is used to check whether the forecast error values remain within acceptable control limits. If no values fall outside the control limits, the method is considered valid and suitable for use as the basis for forecasting the next period.

In the initial research, the Winter method was chosen because it produced the smallest MAPE (20%) and was then validated using the moving range. The validation results showed that no data points were outside the control limits, so the Winter method was considered sufficiently valid for forecasting Product Injection X. After validation, the method was used to generate forecasts for the next 12 periods.

2.8 Conceptual Model

The conceptual model of this research describes the relationship between historical data characteristics, the selection of time series methods, accuracy evaluation, model validation, and forecasting decisions. The main input variable

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is the actual demand data for Injection Product X for the period 2020–2024. This data is analyzed to identify trends and seasonal patterns. The process variables consist of three forecasting methods: Double Moving Average, Double Exponential Smoothing, and Winter Method. These three methods are compared using evaluation metrics such as MAPE, MAD, and MSE. The validation variable is the moving range result, which is used to ensure the stability of the chosen model's error. The output variables are the best forecasting method and the forecast results for the next 12 periods.

Conceptually, this model can be formulated as follows: historical demand data influence the selection of forecasting methods; the forecasting method produces forecast values; the forecast values are compared with actual data to obtain accuracy measures; the method with the best accuracy is validated; and the validated method is used as the basis for demand planning. This model also has managerial implications, as the forecast results can support production planning, inventory control, anticipation of demand surges, and the development of forecasting SOPs. In the initial document, the forecasting SOP emphasizes the stages of collecting a minimum of 12 months of historical data, data validation, trend or seasonal pattern analysis, method selection based on data characteristics, accuracy calculation with a target MAPE of no more than 20%, reporting, and periodic review by the PPIC, production, and marketing teams.

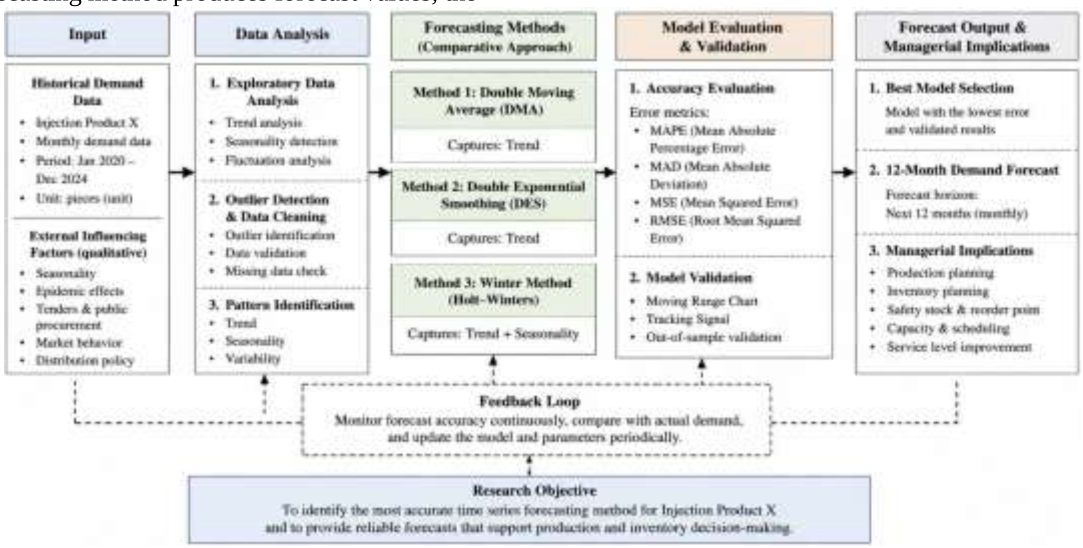

Fig. 1. *Conceptual Framework*

3. RESULTS

3.1 Historical Demand Pattern of Injection Product X

The research results begin with an analysis of the historical demand patterns for Injection Product X during 2020–2024. Analyzing historical patterns is an important initial step in forecasting research because the choice of forecasting method is closely tied to the characteristics of the data. In the context of time series forecasting, demand data must first be examined to determine whether the pattern is horizontal, exhibits a trend, shows extreme fluctuations, indicates seasonality, or contains potential outliers. This procedure aligns with the principles of time series analysis, which hold that data arranged in chronological order should be examined for patterns, trends, and fluctuations before being used to predict future values [1;8;13]. In this study, the actual demand data for Injection Product X were plotted as monthly graphs to observe year-to-year changes in demand.

Based on the actual sales data plot for Product X, demand does not trend steadily but fluctuates across months and years. During some periods, demand increases significantly, while in others it declines sharply. This pattern indicates that the demand for Injection Product X cannot be treated as static data or simple averages. In the pharmaceutical industry, especially for anti-inflammatory and anti-allergy injection products, demand fluctuations can be linked to changing medical needs, possible seasonal patterns, shifts in healthcare facility requirements, and distribution dynamics. Initial findings in the document show that the historical data for Product X from 2020 to 2024 fluctuate, posing challenges for inventory management, as companies must balance the risks of overstocking and stock shortages.

Visually, the actual demand graph also shows a trend and seasonal patterns. The trend pattern is evident in long-term changes in demand, while seasonal indications are seen in recurring fluctuations at certain times. This is important because the chosen forecasting method must align with the data's characteristics. In the literature used in the initial document, if historical data has a trend, then relevant methods are Double Moving Average and Double Exponential Smoothing. If the data exhibits recurring patterns or seasonal trends, the Winter or Holt-Winters methods are more

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appropriate because they account for the level, trend, and seasonal components [1;6;8]. Therefore, the data exploration results support the selection of three main methods in this study, namely Double Moving Average, Double Exponential Smoothing, and Winter Method.

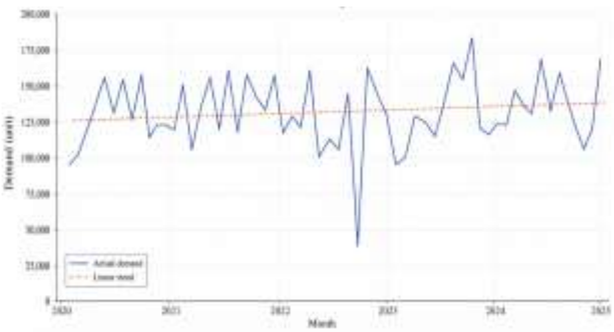

Fig. 2. *Historical Demand Pattern of Injection Product X, 2020–2024*

3.2 Baseline Forecasting Performance before Improvement

Before implementing improvements to the method, the company used a conventional forecasting approach based on simple averaging. This method is relatively easy to apply, but it has a weakness: it does not explicitly account for trend patterns, fluctuations, and seasonality in demand data. Verification results for the initial method showed that the forecasting performance remained low. The obtained Mean Absolute Deviation value was 64,440.388, the Mean Squared Error was 5,200,385,080.091, and the Mean Absolute Percentage Error was 56.211%. Based on the MAPE classification, a value above 50% indicates that the forecasting model is considered poor or inaccurate [8-10]. Therefore, the company's simple averaging method has not provided adequate demand estimates to support production planning and inventory control.

The high MAPE value in the initial method indicates a substantial discrepancy between the forecast results and actual demand. In the context of pharmaceutical operations, this error is not only statistical but also directly impacts production and inventory decisions. If forecast results exceed actual demand, the company may experience overstocking. This condition can increase storage costs, warehouse space usage, and the risk of product expiration. Conversely, if forecast results are lower than actual demand, the company may face understocking or stockouts, which can lead to lost sales opportunities and reduce its ability to meet market needs. The initial document also emphasizes that inaccurate forecasting methods can lead to overstocking or understocking during certain periods, potentially resulting in losses for the company.

This baseline finding provides a strong empirical foundation for evaluating alternative time series methods. In scientific articles, a baseline is necessary to more objectively measure the contribution of the proposed method. Comparing with the initial method shows whether the new model differs only procedurally or truly improves accuracy. With an initial MAPE of 56.211%, the main goal of the research is to develop a method with lower error, particularly one that approaches or falls within the good category based on MAPE interpretation.

Table 1: *Table header*

Forecasting approach	Evaluation period	MAD	MSE	MAPE	Accuracy category	Interpretation
Conventional simple average method	2020–2024	64,440.388	5,200,385,080.091	56.211%	Poor/inaccurate	The existing forecasting approach produced high forecasting errors and was inadequate to support reliable demand planning.

3.3 Forecasting Results Using Double Moving Average

The first method evaluated is the Double Moving Average. This method is used because the demand data for Injection Product X shows a trend. Double Moving Average is an extension of the Moving Average calculated through double moving average computation. According to [1;14], this method calculates the moving average of the moving average, enabling estimation of future demand based on historical data. The Double Moving Average method is designed to minimize forecasting errors compared to the single moving average method, especially for trended data [1;4;5].

In this study, DMA calculation was performed by testing several moving ranges to obtain the most suitable average moving period. Through the iteration process, it was found that a moving range of 4 provided the smallest MAPE value before increasing in the next moving range. Therefore, the DMA method used in this research is based on a 4-period moving average. This choice indicates that the DMA model is applied not only mechanically but also through parameter adjustment based on error performance.

The error recapitulation results show that DMA produced an MSE of 1,148,772,148.650, a MAD of 24,725.948, and a MAPE of 23.477%. Based on the MAPE classification, these values fall within the acceptable range of 20%–50%.

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Compared to the company's initial method, which had an MAPE of 56.211%, DMA provides a significant improvement in accuracy. This decrease in MAPE indicates that the double moving average approach is better at capturing historical demand patterns than the simple average method. Although its performance is better than the initial method, DMA still does not fall into the good category because the MAPE value remains above 20%.

Substantively, the DMA results indicate that trend-based methods can improve forecasting accuracy, but their limitation lies in their ability to capture seasonal patterns. Since Injection Product X shows indications of both trend and seasonality, methods that only consider the trend cannot fully capture the demand dynamics. Therefore, DMA methods can be viewed as a better alternative compared to the baseline, but they are not the best method in this study.

3.4 Forecasting Results Using Double Exponential Smoothing

The second method evaluated is Double Exponential Smoothing. This method was chosen because it is relevant to trended data. Double Exponential Smoothing performs smoothing twice to account for differences between historical data and forecast results. DES is used when the data pattern shows a trend by adding the second smoothing value to the first [1;4;5]. DES is suitable for trend-patterned data through a double smoothing process [9;10], while [1] emphasizes that DES can handle trend changes and fluctuations by giving greater weight to the most recent data.

The evaluation results show that the DES yields an MSE of 1,457,660,356.039, a MAD of 29,570.161, and a MAPE of 25.825%. Based on the MAPE classification, this method is considered feasible. Compared with the simple average baseline, DES reduced the MAPE from 56.211% to 25.825%. This indicates that the double exponential smoothing method is superior to conventional methods because it is more responsive to changes in the data. However, compared with DMA, DES error values remain higher. The DES MAPE of 25.825% is higher than the DMA MAPE of 23.477%, and the DES MSE and MAD are also larger than those of DMA.

This performance difference indicates that although DES is theoretically suitable for trended data, it is not yet optimal for capturing the pattern of Injection Product X. One possible reason is the presence of seasonal components that DES does not explicitly account for

In other words, DES can improve accuracy over simple averaging methods, but its performance remains limited when the data exhibit fluctuations, trends, and seasonal patterns. In the standards for scientific article reporting, such results are important to present comparatively because they demonstrate that the theoretical suitability of a method must be confirmed through empirical performance.

3.5 Forecasting Results Using the Winter Method

The third method tested is the Winter (Holt-Winters) method. This method offers greater comprehensiveness than DMA and DES because it explicitly accounts for level, trend, and seasonality. The Winter (Holt-Winters) method is the most suitable time-series forecasting technique for data with clear trends and seasonal patterns [1;6;8]. Since the Injection Product X data plot shows a tendency toward trend and seasonal patterns, this method is theoretically a strong candidate for achieving the best accuracy.

The results of the Winter Method calculation show an MSE value of 718,965,593, an MAD of 20,157, and a MAPE of 20%. Based on the MAPE classification, this method falls into the good category. The MAPE of 20% also indicates that the Winter Method performs best compared to DMA and DES. Additionally, the MSE and MAD values for the Winter Method are the lowest among all the tested methods. This demonstrates that the Winter Method not only yields lower percentage errors but also smaller absolute and squared errors.

The advantage of the Winter Method in this research is consistent with its theoretical characteristics. Because the demand for Injection Product X exhibits a fluctuating pattern with trend and seasonal components, a method that explicitly accounts for seasonal components is better able to capture the dynamics of historical data. Compared to DMA, which focuses more on trend using moving averages, and DES, which emphasizes trend using exponential smoothing, the Winter Method has a structure better suited to demand data that changes periodically. Therefore, these results reinforce the argument that the choice of forecasting method should be based on the characteristics of the data pattern, not just on ease of calculation.

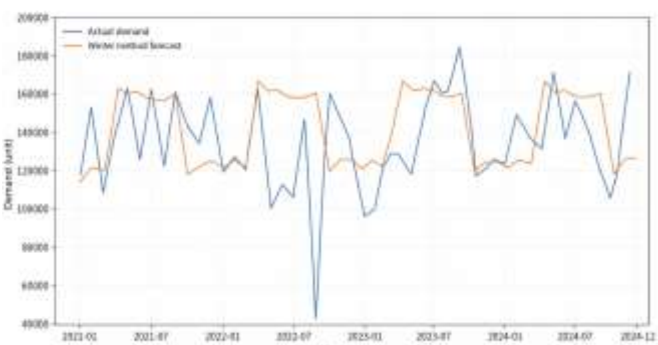

Fig. 3. *Actual Demand versus Winter Method Forecast*

3.6 Comparative Forecasting Performance

To present the results more systematically, all methods are compared based on three main metrics: MSE, MAD, and MAPE. Presenting a performance comparison of several methods in a single table is a relevant practice in forecasting studies because it allows readers to assess the relative advantages of each method transparently. In this study, DES yields an MSE of 1,457,660,356.039, MAD of 29,570.161, and MAPE of 25.825%; DMA produces an MSE of

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1,148,772,148.650, MAD of 24,725.948, and MAPE of 23.477%; while the Winter Method results in an MSE of 718,965,593, MAD of 20,157, and MAPE of 20%.

Based on the results, the performance order of the methods from best to worst is Winter Method, DMA, and DES. The Winter Method has the smallest error across all metrics, making it the best forecasting method. Compared to the company's baseline, the Winter Method reduces the MAPE from 56.211% to 20%. This reduction indicates a substantial improvement in accuracy. Practically, this decrease in error can reduce the risk of errors in determining production quantities and inventory levels.

The interpretation of MAPE becomes an important aspect in this analysis. Based on the classification used in the initial document, a MAPE of less than 10% indicates a very good model, 10%–20% indicates a good model, 20%–50% indicates a fair model, and more than 50% indicates a poor model. Therefore, the company's initial method falls into the poor category, DES and DMA are in the fair category, while the Winter Method is on the border of the good category. Although the MAPE of the Winter Method is exactly 20%, this result still represents a significant improvement over the initial method and the other comparison methods.

Table 2: *Forecasting Accuracy Results of DMA, DES, and Winter Method*

Forecasting method	MSE	MAD	MAPE	Accuracy category	Rank	Interpretation
Double Exponential Smoothing (DES)	1,457,660,356.039	29,570.161	25.825%	Acceptable	3	DES improved the baseline forecasting performance but produced the highest error among the three time-series methods.
Double Moving Average (DMA)	1,148,772,148.650	24,725.948	23.477%	Acceptable	2	DMA generated lower forecasting errors than DES, indicating better suitability for demand data with a trend component.
Winter Method / Holt-Winters	718,965,593.000	20,157.000	20.000%	Good	1	Winter Method produced the lowest MSE, MAD, and MAPE, indicating the best forecasting performance for demand data with trend and seasonal patterns.

3.7 Validation of the Selected Forecasting Method

After the Winter Method was chosen as the best based on the smallest error, the next step was to validate the model using the moving range. Validation is conducted to ensure that the model not only achieves the highest numerical accuracy but also produces error patterns that remain within control limits. In time series forecasting research, validation is important for assessing the stability of forecasting results and ensuring that the model is suitable for predicting the next period.

The validation results show an average moving range value of 33,682.51158. Based on this value, the upper control limit (UCL) is 89,595.478, and the lower control limit (LCL) is -89,595.478. The validation graph indicates that no data points are outside the control limits. There are no values greater than the UCL or less than the LCL. Therefore, the Winter method has passed the validation test and is suitable for forecasting demand for Injection Product X in the next period.

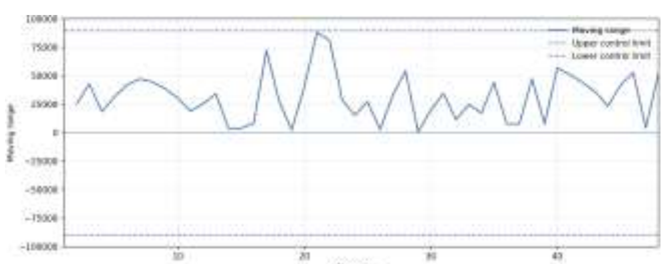

Fig. 4. *Twelve-Month Demand Forecast for Injection Product X*

This validation result reinforces previous findings that the Winter Method is the most suitable approach. If a model has a low error value but produces unstable error patterns or many points outside the control limits, then the model needs to be reviewed. However, in this study, the Winter Method not only has the lowest MAPE, MAD, and MSE but also demonstrates error stability with respect to moving range. Therefore, the selection of the Winter Method has a stronger empirical basis.

Table 3 *Validation Results of the Selected Forecasting Method*

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Selected forecasting method	Validation technique	Mean moving range	Upper Control Limit	Lower Control Limit	Validation result	Interpretation
Winter Method / Holt-Winters	Moving Range Chart	33,682.511	89,595.478	-89,595.478	Valid	All forecasting errors were within the control limits; therefore, the selected Winter Method was considered stable and suitable for forecasting the next period.

3.8 Twelve-Month Forecasting Results

After the Winter method was declared valid, it was used to forecast demand for Injection Product X over the next 12 periods. The forecast results showed the following demand values: 116,237, 124,515, 120,244, 171,099, 161,044, 165,433, 159,828, 160,036, 163,616, 116,196, 125,652, and 125,674. The highest demand is estimated to occur in the fourth period at 171,099 units, while the lowest is in the tenth period at 116,196 units. The initial document notes that the results of this 12-period forecast can be used as the basis for the 2025 production policy.

Presenting the forecast results for the next 12 periods is important because the forecasts must translate into operational decisions. In the context of production planning, the forecast value can serve as the basis for preparing monthly production schedules, capacity planning, and raw material requirement estimates. During periods with high demand predictions, such as periods four through nine, the company needs to ensure production capacity readiness, raw material availability, and distribution preparedness. Conversely, during periods with lower demand, such as periods one and ten, the company can adjust production more carefully to avoid excess inventory.

The forecast results are also relevant for inventory control. Monthly forecasts can be used to calculate safety stock requirements, determine reorder points, and anticipate discrepancies between actual demand and production plans. Because pharmaceutical products have expiration risks, inventory decisions focus not only on meeting demand but also on managing shelf life and storage costs. Therefore, more accurate forecast results can help companies reduce the risks of overstocking and stockouts simultaneously.

Table 4. Twelve-Month Demand Forecast for Injection Product X

Forecasting period	Forecasted demand (unit)	Managerial interpretation
1	116,237	Relatively moderate demand; production can be planned cautiously to avoid overstock.
2	124,515	Moderate demand; maintain regular production and inventory replenishment.
3	120,244	Moderate demand; inventory should be monitored to prevent unnecessary stock accumulation.
4	171,099	The highest forecasted demand, production capacity, and material availability should be prepared in advance.
5	161,044	High demand; requires sufficient production planning and inventory readiness.
6	165,433	High demand; ensure adequate raw material supply and production scheduling.
7	159,828	High demand; maintain sufficient safety stock to reduce the risk of stockouts.
8	160,036	High demand: inventory and distribution plans should align with demand expectations.
9	163,616	High demand; production planning should anticipate continued elevated demand.
10	116,196	Lowest forecasted demand; production volume should be controlled to avoid excess inventory.
11	125,652	Moderate demand; maintain balanced inventory and replenishment planning.
12	125,674	Moderate demand; suitable for regular production planning and inventory review.

3.9 Operational Implications of the Forecasting Results

The main findings of this study indicate that using a time-series method appropriate to the data's characteristics can improve the quality of demand forecasting. The Winter Method proved to be the most accurate because it can capture trend and seasonal components. From an operational perspective, these results provide a basis for companies to shift their forecasting process from a conventional simple-average approach to a data-driven approach grounded in historical data and error evaluation.

The first implication relates to production planning. With a 12-period forecast, the production department can develop a more realistic capacity plan. High-demand periods can be prepared for by increasing production schedules, adjusting the workforce, and ensuring raw material availability. The second implication concerns inventory management. The logistics and inventory departments can use the forecast results to determine optimal inventory levels, reduce the risk of overstocking, and maintain product availability during periods of increased demand. The third implication involves cross-functional coordination. The forecast results need to be communicated to the PPIC, production, marketing, and distribution functions to ensure demand planning is not done in isolation.

Overall, the research results show that the Winter Method is the most suitable approach for forecasting the demand for Injection Product X. This finding not only demonstrates a statistically significant increase in accuracy but also provides a practical basis for the company to improve its demand planning process, reduce inventory error risks, and develop a more structured forecasting SOP.

4. Discussion

Research results indicate that selecting a forecasting method aligned with the characteristics of the data pattern has a significant impact on improving the accuracy of demand forecasts for Injection Product X. The actual data plot for the 2020–2024 period shows the presence of trend and seasonal patterns, making the use of time series methods relevant to replace conventional approaches based on simple averages. This finding aligns with the fundamental principles of time series analysis, which state that data recorded over specific time intervals should be analyzed based on historical patterns, trends, fluctuations, and seasonal components before being used to project future demand [1;8;13]. In this context, the forecasting method cannot be chosen solely on the basis of ease of calculation; it must also consider the compatibility between the model structure and the characteristics of the demand data. Injection Product X data, which is volatile, trend-prone, and exhibits seasonal indications, requires a method capable of capturing both changes in demand levels and recurring patterns over time.

The comparison among the Double Exponential Smoothing method, Double Moving Average, and Winter Method shows that the Winter Method achieves the highest accuracy. DES yields a MAPE of 25.825%, DMA yields a MAPE of 23.477%, while the Winter Method results in a MAPE of 20%, MAD of 20.157, and MSE of 718,965,593. Based on the MAPE classification, the Winter method falls into the good category, while DES and DMA are in the acceptable category. This difference indicates that methods that explicitly account for seasonal components are more suitable for the demand data for Injection Product X than methods primarily oriented toward trend. DMA is designed for trend-based data using a double moving average mechanism [1;14], whereas DES is relevant for trend-patterned data through a double smoothing process [1;4;5]. However, both methods have limitations when demand patterns are influenced not only by trends but also by seasonal variations. Conversely, the Winter Method, or Holt-Winters, is theoretically superior because it integrates level, trend, and seasonal components into a single forecasting framework [1;6;8].

The advantages of the Winter Method in this study also show that forecasting accuracy depends heavily on the model's ability to represent actual demand dynamics. In the pharmaceutical industry, especially for anti-inflammatory and anti-allergy injection products, demand can fluctuate due to seasonal factors, changes in healthcare facility needs, disease outbreaks, distribution policies, and market purchasing patterns. Injection products have more critical characteristics than general manufacturing products because their availability is directly tied to medical needs and healthcare services. Therefore, forecasting errors not only impact the company's internal efficiency but also affect its ability to meet customer and healthcare facility needs. The finding that the Winter Method can reduce MAPE from 56.211% to 20% demonstrates that applying the appropriate time-series method can substantially improve the quality of demand information. The initial method, based on simple averaging, was considered inaccurate because it produced an MAPE above 50%, whereas the Winter Method brought forecasting performance into the good category.

Validation using the moving range strengthens the feasibility of the Winter Method as the preferred method. The validation results show an average moving range value of 33,682.51158, with an upper control limit of 89,595.478 and a lower control limit of -89,595.478. No data points fall outside the control limits, so the Winter Method is declared valid. This finding is important because a good forecasting model is determined not only by the lowest error value but also by its error stability. In forecast validation practice, the stability of the results serves as a basis to ensure that the model does not produce extreme deviations that could disrupt production and inventory decisions. Therefore, the Winter Method not only performs well with respect to MAPE, MAD, and MSE but also meets the error-stability criteria based on the moving range.

The managerial implications of increased forecasting accuracy are very important for pharmaceutical supply chain management. The 12-period forecast generated using the Winter Method provides a quantitative basis for the company to develop its 2025 production plan. The forecast results indicate a monthly demand of 116,237; 124,515; 120,244; 171,099; 161,044; 165,433; 159,828; 160,036; 163,616; 116,196; 125,652; and 125,674 units. The highest demand is in the fourth period, at 171,099 units, while the lowest is in the first period, at 116,237 units. This information can be used to adjust production capacity, raw material procurement, labor needs, and distribution plans. During high-demand periods, the company needs to ensure capacity readiness and the availability of raw materials to prevent stockouts. During periods of low demand, the company should control production to avoid overstocking, which can increase storage costs and the risk of product expiration.

Improving forecast accuracy also increases service level. In the pharmaceutical industry, the service level not only reflects the company's ability to meet customer demand but also indicates the reliability of the distribution system in ensuring the availability of healthcare products. High forecasting errors can lead to two main consequences: excess inventory and stockouts. Excess inventory impacts storage costs, warehouse space utilization, and the risk of product expiration, while stockouts can result in lost sales opportunities and failure to meet the demand of healthcare facilities. Therefore, more accurate forecast results can serve as a basis for determining safety stock, reorder points, production schedules, and capacity allocation more rationally. By using monthly forecast results, companies can develop more anticipatory inventory control systems rather than reactive ones.

In addition to technical aspects, the research results emphasize the importance of institutionalizing the forecasting process through Standard Operating Procedures (SOPs) and a structured demand planning mechanism. The proposed SOP in the document states that forecasting aims to support the company's decision-making, covering everything from collecting historical data to evaluating forecast results and implementing decisions, and requires valid, complete, and documented data. The SOP also specifies that forecasting methods should be chosen based on their suitability to data patterns and resource availability, with responsible parties including PPIC staff, PPIC Managers, and Production Managers. The proposed performance indicators include meeting all customer demands and forecast accuracy with a Mean Absolute Percentage Error (MAPE) of no more than 20%.

This SOP is important because effective forecasting not only depends on mathematical models but also on cross-functional coordination. A structured forecasting process can strengthen relationships between PPIC, production, marketing, logistics, and inventory management. The marketing department can provide information on market demand dynamics; the PPIC department translates the forecast into a production plan and material requirements; the production department adjusts capacity, while the logistics and inventory departments ensure product availability according to needs. The recommendations in the document also emphasize the need for monthly reviews by a collaborative team comprising PPIC, production, and marketing to evaluate deviations between forecast results and actual sales, as well as training in time series methods and the use of software such as Minitab. Thus, the main contribution of this research is not only the selection of the Winter Method as the best method but also the provision of a foundation for improving demand planning systems that are more data-driven, validated, and well-coordinated.

5. CONCLUSION

This research shows that the accuracy of demand forecasting plays an important role in supporting production planning and inventory control, and in improving service levels in the pharmaceutical industry. The demand characteristics of the Injection X product fluctuate, with indications of trends and seasonal patterns. These characteristics make conventional forecasting methods based on simple averages inadequate for producing accurate demand estimates. Initial evaluation results indicate that the method previously used by the company produced a Mean Absolute Percentage Error of 56.211%, a Mean Absolute Deviation of 64.440.388, and a Mean Squared Error of 5,200,385,080.091. These values suggest that the initial method is inaccurate and could pose operational risks, including overstocking, stockouts, increased storage costs, product expiration, and lost sales opportunities.

A comparison of three time series forecasting methods shows that the Winter Method, or Holt-Winters, performs best, outperforming Double Moving Average and Double Exponential Smoothing. Double Exponential Smoothing results in a Mean Absolute Percentage Error of 25.825%, Double Moving Average of 23.477%, while the Winter Method yields a Mean Absolute Percentage Error of 20%, a Mean Absolute Deviation of 20.157, and a Mean Squared Error of 718,965,593. These findings indicate that the Winter Method is better suited to the demand pattern of Injection Product X because it can simultaneously account for the level, trend, and seasonal components. Therefore, the research results reinforce the argument that forecasting methods should be chosen based on the characteristics of historical data, not solely on ease of implementation.

Model validation using the moving range reinforces the conclusion that the Winter Method is suitable for use as the selected forecasting method. The absence of error values outside the control limits indicates that the model has adequate error stability. After validation, the Winter Method is used to forecast demand for the next 12 periods. These forecast results provide a quantitative basis for the company to develop monthly production plans, adjust capacity, plan raw material needs, determine inventory levels, and anticipate periods of high or low demand.

The managerial implications of this research are quite significant. Improved forecasting accuracy can help companies reduce the risks of overstocking and stock shortages. During periods of high demand, forecast results can be used to ensure readiness of production capacity and raw material availability, and to ensure smooth distribution. Conversely, during periods of lower demand, forecast results can help companies control production to prevent excessive inventory accumulation. In the context of pharmaceutical products, these implications are especially important because inventory is linked not only to costs but also to product shelf life, quality compliance, and the company's ability to meet healthcare facilities' needs.

This research also emphasizes the importance of institutionalizing the forecasting process through SOPs and a structured demand planning mechanism. An accurate forecasting model will not deliver optimal benefits without clear cross-functional processes. Therefore, the results of this study need to be integrated into the coordination among PPIC, production, marketing, logistics, and inventory management. A forecasting SOP based on historical data, method validation, accuracy evaluation, and periodic review can help the company build a more consistent, well-documented, and adaptable demand planning system in response to market changes.

Scientifically, this study contributes to the body of knowledge on the application of time-series forecasting in the pharmaceutical industry, particularly at the individual product or SKU level. Most forecasting studies often focus on general products, retail, energy, or aggregate data, whereas this study places injectable pharmaceutical products as the object of analysis, which have critical demand characteristics. By comparing the Double Moving Average, Double Exponential Smoothing, and Winter Method, this research provides empirical evidence that methods that account for trends and seasonality are more appropriate for the fluctuating demand for pharmaceutical products. The practical contribution lies in providing a basis for improving the company's forecasting processes by recommending the best methods and strengthening forecasting SOPs.

Nevertheless, this study has several limitations. The analysis was conducted on only one injection product and used a time-series approach based on internal historical data. This research has not yet included external variables such as changes in disease patterns, epidemics, allergy seasons, government tenders, promotions, prices, distribution policies, or sales channel dynamics. Future research could expand the scope to include several pharmaceutical products with different demand characteristics, compare the Winter method with ARIMA, SARIMA, dynamic regression, machine learning, or hybrid models, and incorporate external variables to improve the models' accuracy and explanatory power. Additionally, subsequent studies could develop forecasting models linked to decisions on safety stock, reorder points, production capacity, and sales and operations planning, thereby enabling a more comprehensive measurement of forecasting's contribution to the performance of the pharmaceutical supply chain.

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