

Analysis of The Effectiveness and Accuracy of A Production System Based on Demand Forecasting in Reducing Excess Stock

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Abstract: This study analyzes the effectiveness and accuracy of a demand forecasting-based production system to reduce excess stock at the *Ayam Geprek Bu Novi* culinary business on Jl. Bukit Barisan. Using a quantitative approach, the research applies a time series forecasting method with three main techniques: Moving Average (MA), Weighted Moving Average (WMA), and Exponential Smoothing (ES). Weekly demand data from February to May 2025 were collected and analyzed to measure prediction accuracy and evaluate its impact on raw material efficiency. The results reveal that the 3-week WMA method provides the highest responsiveness to increasing demand trends and yields forecasts closest to actual sales, while the 6-week MA and ES with $\alpha = 0.2$ show more stable performance under less fluctuating demand. Implementing these simple Excel-based forecasting models enables micro, small, and medium culinary enterprises (MSMEs) to better align production with demand, thereby minimizing overstock and improving operational efficiency. This study demonstrates that data-driven decision-making through easy-to-use forecasting tools can significantly support MSMEs in optimizing inventory control and maintaining production sustainability. The findings provide practical insights for small fast-food businesses seeking adaptive inventory management solutions without requiring complex systems or high implementation costs.

Keywords: Demand Forecasting, Moving Average, Weighted Moving Average, Inventory Management

Abstrak: Studi ini menganalisis efektivitas dan akurasi sistem produksi berbasis peramalan permintaan untuk mengurangi kelebihan stok pada usaha kuliner Ayam Geprek Bu Novi di Jl. Bukit Barisan. Dengan menggunakan pendekatan kuantitatif, penelitian ini menerapkan metode peramalan deret waktu dengan tiga teknik utama: Moving Average (MA), Weighted Moving Average (WMA), dan Exponential Smoothing (ES). Data permintaan mingguan dari Februari hingga Mei 2025 dikumpulkan dan dianalisis untuk mengukur akurasi prediksi dan mengevaluasi dampaknya terhadap efisiensi bahan baku. Hasilnya mengungkapkan bahwa metode WMA 3 minggu memberikan respons tertinggi terhadap tren peningkatan permintaan dan menghasilkan peramalan yang paling dekat dengan penjualan aktual, sementara MA 6 minggu dan ES dengan $\alpha = 0,2$ menunjukkan kinerja yang lebih stabil di bawah permintaan yang kurang berfluktuasi. Menerapkan model peramalan berbasis Excel yang sederhana ini memungkinkan usaha kuliner mikro, kecil, dan menengah (UMKM) untuk lebih menyelaraskan produksi dengan permintaan, sehingga meminimalkan kelebihan stok dan meningkatkan efisiensi operasional. Studi ini

menunjukkan bahwa pengambilan keputusan berbasis data melalui perangkat peramalan yang mudah digunakan dapat secara signifikan mendukung UMKM dalam mengoptimalkan pengendalian inventaris dan menjaga keberlanjutan produksi. Temuan ini memberikan wawasan praktis bagi bisnis makanan cepat saji skala kecil yang mencari solusi manajemen inventaris adaptif tanpa memerlukan sistem yang rumit atau biaya implementasi yang tinggi.

Kata kunci : Peramalan Permintaan, Rata-Rata Bergerak, Rata-Rata Bergerak Tertimbang, Manajemen Inventaris

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Introduction

Ayam geprek (smashed chicken) is a rapidly growing culinary product in Indonesia. Its distinctive taste, affordable price, and ease of preparation make this dish popular with a wide range of people. High consumer demand has encouraged many micro-enterprises to open their own fried chicken businesses. However, despite this growth, many similar businesses are unable to survive due to weak production planning and non-data-driven inventory management. Inaccurate daily demand forecasts often lead to overproduction and stockouts, which result in wasted raw materials and decreased customer satisfaction.

This problem is also experienced by the Ayam Geprek Bu Novi MSME on Jl. Bukit Barisan, Medan. This business faces high daily demand fluctuations without a systematic sales recording system. Stockouts are common on certain days, such as Fridays and Saturdays, while at the beginning of the week, many products go unsold and are ultimately wasted. This situation highlights the need for a simple yet accurate demand forecasting system to adjust production levels to actual needs. By implementing appropriate forecasting methods, businesses are expected to reduce raw material waste, increase production efficiency, and maintain operational stability.

Table 1 below displays the results of observations of production and demand data for geprek chicken at Ayam Geprek Bu Novi's stall for 10 consecutive days in September 2025. Data were collected directly from daily sales records to illustrate the pattern of mismatch between production and actual demand. However, this relatively limited sample size is used only for initial illustration and is not yet representative of the overall long-term demand pattern.

Table 1: The following is the observation data for 10 days in February 2025:

Day	Chicken Production (KG)	Actual Demand (KG)	Difference	Information
Monday	70	55	+15	Overproduction
Tuesday	65	58	+7	Overproduction
Wednesday	70	69	+1	Appropriate
Thursday	75	81	-6	Weaknesses
Friday	80	92	-12	Weaknesses
Saturday	90	100	-10	Weaknesses
Sunday	85	87	-2	Weaknesses
Monday	70	54	+16	Overproduction
Tuesday	65	60	+5	Overproduction
Wednesday	70	72	-2	Weaknesses

Source: Observation Results

Conceptually, quantitative forecasting methods such as Moving Average (MA), Weighted Moving Average (WMA), and Exponential Smoothing (ES) are widely used due to their simplicity and ability to identify demand patterns based on historical data. Stevenson (2020) stated that forecast accuracy significantly impacts the efficiency of production systems and supply chain management, particularly in the fast food sector, which experiences high demand volatility. Although this method is widely used, its implementation at the micro-business scale has rarely been empirically studied, especially in the context of daily operations based on simple data such as Microsoft Excel. This type of solution is crucial for MSMEs that lack access to sophisticated analytical software.

Several previous studies have focused on the technical aspects of forecasting accuracy, but few have discussed its practical application in the daily production processes of culinary MSMEs. Therefore, this study seeks to fill this gap by analyzing the effectiveness and accuracy of a demand forecasting-based production system using three simple methods: MA, WMA, and ES, at Ayam Geprek Bu Novi. This study aims to assess the extent to which these methods can reduce excess inventory, increase raw material efficiency, and support data-driven production decision-making. The results are expected to provide practical contributions to other culinary

MSMEs in developing adaptive, efficient, and sustainable production planning systems.

Methods

This research uses a descriptive quantitative approach with a case study method on the Ayam Geprek Bu Novi culinary business in Medan. Case studies in quantitative research are used to gain in-depth empirical understanding of a single unit of analysis without the aim of generalizing to the population (Yin, 2018). Although case studies are more commonly used in qualitative research, their quantitative application remains valid when the focus of the research is to generate applicable findings in a specific context (Creswell & Creswell, 2018). Therefore, this combination of approaches was chosen to measurably map demand patterns and production systems in one MSME.

The forecasting methods used included Moving Average (MA), Weighted Moving Average (WMA), and Exponential Smoothing (ES), as recommended in the time series forecasting literature (Makridakis, Wheelwright, & Hyndman, 1998). Technical parameters were explicitly described to ensure the study's replication. The MA period was set at $n = 3$ weeks to capture short-term demand changes. The WMA weights were set at 0.5, 0.3, and 0.2 based on the principle that the most recent data has the greatest influence on projections (Hyndman & Athanasopoulos, 2021). The α value for the ES was determined at 0.3 by testing several candidate values between 0.1 and 0.5, in accordance with recommendations for selecting smoothing parameters that minimize error (Gardner, 2006). Parameter determination was carried out systematically to ensure transparent and retestable calculations.

The research data were obtained from cash books and daily sales records, which were cross-checked with raw material stock records—a procedure commonly used in validating MSME operational data (Saunders, Lewis, & Thornhill, 2019). Missing data were handled through simple linear interpolation, a method commonly used in time series when data gaps are relatively small (Chatfield, 2004). All data were then aggregated into weekly data to stabilize demand patterns. There were a total of 16 weeks of observation, and this sample size was justified based on the limited MSME data period and the applied, rather than inferential, purpose of the study.

The data was divided into 75% training data and 25% testing data, following standard practice in forecasting model evaluation (Hyndman & Athanasopoulos, 2021). Accuracy was evaluated using Mean Absolute Deviation (MAD) and Mean Square Error (MSE), as they are more stable for small-scale demand data and focus on the number of physical units, rather than the percentage error (Makridakis et al., 1998). Although MAPE and RMSE were mentioned in the introduction, MAD and

MSE were chosen because they are more appropriate for MSME production with relatively low daily demand variation.

This study has several limitations, including the use of a single case, which limits generalizability (Yin, 2018), the failure to account for seasonal variables due to limited data length, and the relatively short sample size (16 weeks). Therefore, the research results are more contextual and applicable, and their application is recommended for businesses with similar characteristics.

Result and Discussion

Results

Moving Average

Date	Actual Demand	Ma 3 Weeks	Forecasting With MA 3 Weekly	MA 6 Weekly	Forecasting with Weekly 6 MA
01 – 07 Feb 2025	360				
08 – 14 Feb 2025	375				
15 – 21 Feb 2025	390	375			
22 – 28 Feb 2025	405	390	375		
01 – 07 March 2025	415	403,3333333	389,4444444		
08 – 14 March 2025	430	416,6666667	403,3333333	395,8333333	
15 – 21 March 2025	440	428,3333333	416,1111111	409,1666667	395,8333333
22 – 28 March 2025	450	440	428,3333333	421,6666667	421,6666667
29 March – 04 Apr 2025	460	450	439,4444444	433,3333333	433,3333333
05 – 11 Apr 2025	470	460	450	450	444,1666667
12 – 18 Apr 2025	455	461,6666667	457,2222222	450,8333333	450,8333333
19 – 25 Apr 2025	440	455	458,8888889	452,5	452,5
26 Apr – 02 May 2025	460	451,6666667	456,1111111	455,8333333	455,8333333
03 – 09 May 2025	475	458,3333333	455	460	460

10 – 16 May 2025	480	471,6666667	460,5555556	463,3333333	463,3333333
17 – 23 May 2025	490	481,6666667	470,5555556	466,6666667	466,6666667
24 – 30 May 2025	500	490	481,1111111	474,1666667	474,1666667

Table 2 moving average**Source: Excel,(2025)****Weighted Moving Average**

The demand forecasting for *Ayam Geprek Bu Novi* was conducted using the *Weighted Moving Average* (WMA) method with a 3-week period (WMA-3). This method provides a higher weight to more recent data to improve the model's responsiveness to short-term changes in demand trends.

The results of the WMA-3 calculation show that the method was able to follow the actual demand pattern closely throughout the observation period, from February to the end of May 2025. The forecast values tended to increase progressively in line with the upward trend in actual demand. For example, in the week of March 8–14, 2025, the WMA forecast reached 420 kg, which was very close to the actual demand of 430 kg. This indicates that the WMA method effectively captured the short-term fluctuations and ongoing upward trend in demand.

Furthermore, during a period of significant increase in demand—such as the week of May 17–23, 2025—the WMA value rose to 483.75 kg, closely reflecting the actual demand of 490 kg. This shows that the weighting factor in the WMA allows the forecast to adjust more quickly to recent changes compared to the simple Moving Average (MA).

Overall, the application of WMA with a 3:2:1 weighting ratio produced accurate and stable forecast results. The weighted approach successfully emphasized the importance of recent data, resulting in forecast values that were consistently close to the actual demand. This finding demonstrates that the WMA method is highly suitable for business environments with fluctuating or upward-trending demand patterns, such as in the culinary sector.

Table 3: weighted moving average

Date	Actual Demand	3 weekly WMA
01 – 07 Feb 2025	360	
08 – 14 Feb 2025	375	
15 – 21 Feb 2025	390	378,75
22 – 28 Feb 2025	405	393,75

01 – 07 Mar 2025	415	406,25
08 – 14 Mar 2025	430	420
15 – 21 Mar 2025	440	431,25
22 – 28 Mar 2025	450	442,5
29 Mar – 04 Apr 2025	460	452,5
05 – 11 Apr 2025	470	462,5
12 – 18 Apr 2025	455	460
19 – 25 Apr 2025	440	451,25
26 Apr – 02 May 2025	460	453,75
03 – 09 May 2025	475	462,5
10 – 16 May 2025	480	473,75
17 – 23 May 2025	490	483,75
24 – 30 May 2025	500	492,5

Source: Excel (2025)

Exponential Smoothing**Table 4 Exponential Smoothing**

Date	Actual Demand	$\bar{y} \times A_t$ $\bar{y}=0.2$	$(1 - \bar{y}) \times F_{t-1}$	Exponential 1 smoothing	forecasting with ES (F_t)
01 – 07 Feb 2025	360				
08 – 14 Feb 2025	375			450	
15 – 21 Feb 2025	390	75	360	435	450
22 – 28 Feb 2025	405	78	348	426	435
01 – 07 March 2025	415	81	340,8	421,8	426
08 – 14 March 2025	430	83	337,44	420,44	421,8

15 - 21 March 2025	440	86	336,352	422,352	420,44
22 - 28 March 2025	450	88	337,8816	425,8816	422,325
29 March - 04 Apr 2025	460	90	340,70528	430,70528	425,8816
05 - 11 Apr 2025	470	92	344,564224	436,564224	430,70528
12 - 18 Apr 2025	455	94	349,2513792	443,2513792	436,564224
19 - 25 Apr 2025	440	91	354,6011034	445,6011034	443,2513792
26 Apr - 02 May 2025	460	88	356,4808827	444,4808827	445,6011034
03 - 09 May 2025	475	92	355,5347062	447,5847062	444,4808827
10 - 16 May 2025	480	95	358,0677649	453,0677649	447,5847062
17 - 23 May 2025	490	96	362,4542119	458,4542119	453,0677649
24 - 30 May 2025	500	98	366,7633695	464,7633695	458,4542119

Source: Excel (2025)

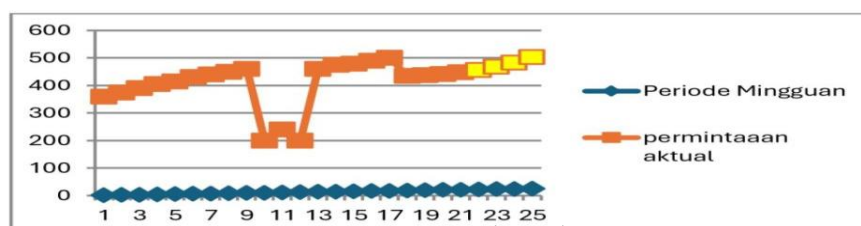
The *Exponential Smoothing* method is one of the most widely used time series forecasting techniques due to its simplicity and effectiveness in handling fluctuating demand data. Unlike the *Moving Average* method, *Exponential Smoothing* is more suitable for data without strong seasonal or trend components and is commonly applied in operations planning, inventory management, and production forecasting (Hyndman & Athanasopoulos, 2021). In this study, the *Single Exponential Smoothing* (SES) method was applied with a smoothing parameter of $\alpha = 0.2$ to forecast weekly demand data from February to May 2025. The results indicate that this method was able to capture the overall demand pattern effectively. Although the forecast values tended to slightly lag behind actual demand increases, the method demonstrated stability and smoothness in its projection.

For instance, during the week of March 1–7, 2025, the actual demand reached 415 kg, while the forecasted value was 421.8 kg, showing a close and consistent upward trend. In the final week of observation (May 24–30, 2025), the forecasted value reached 464.76 kg, whereas the actual demand was 500 kg. This shows that although the method was slower in responding to sudden demand surges, it still followed the overall increasing trend quite well.

The primary advantage of the *Exponential Smoothing* method lies in its computational simplicity and its ability to produce smooth forecasts without sharp fluctuations. This makes it particularly suitable for short-term data without strong trends or seasonal patterns. However, one limitation of the method is its delayed response to sudden changes or emerging trends, especially when the smoothing parameter (α) is set to a low value. In this case, the chosen value of $\alpha = 0.2$ produced stable results but was relatively slow in capturing the sharp increase in demand during May. A higher α value could improve responsiveness but might also introduce greater variability in the forecasts (Nahmias & Olsen, 2020).

Overall, the results of applying *Exponential Smoothing* with $\alpha = 0.2$ demonstrate that this method is effective in producing stable and relatively accurate forecasts that align with the actual weekly demand trend. Despite its slower reaction to sudden demand spikes, the method successfully represented the gradual upward pattern throughout the observation period. Therefore, *Exponential Smoothing* is suitable for operational planning contexts where demand patterns are relatively stable and non-seasonal.

Graph 1 demand forecasting forecast



Source: Excel (2025)

Forecasting Error

The forecasting method with the smallest error value is the most accurate. Forecast accuracy is determined by the forecast error value. The following are the results of the forecasting error calculation above:

Table 5 Forecasting Error Analysis

MAD	RMSE	MAPE
4	22.45033902	8

Source: Excel (2025)

The forecasting method with the smallest error value is considered the most accurate. Forecast accuracy is determined by the magnitude of the forecast error. The results of the error calculation are presented as follows. The calculation results show that the forecasting method used demonstrates a relatively high level of accuracy. The Mean Absolute Deviation (MAD) value of 4 indicates that the average absolute difference between the actual data and the forecasted values is very small, suggesting

that the predictions are quite close to the real observations. The Root Mean Square Error (RMSE) value of 22.45 further supports this finding, showing that the average squared deviation is within an acceptable range, though slightly larger than the MAD due to the squaring of larger errors.

Meanwhile, the Mean Absolute Percentage Error (MAPE) value of 8% indicates that the average forecasting error represents only 8% of the actual demand. This result reflects a high level of forecasting accuracy, as it falls below the commonly accepted threshold of 10%, which is typically used to categorize a forecast as *very good* (Hyndman & Athanasopoulos, 2021). Overall, these evaluation metrics confirm that the forecasting approach applied in this study produces reliable and accurate predictions that can effectively support production and inventory planning decisions.

The results of this study using the three forecasting methods – Moving Average (MA), Weighted Moving Average (WMA), and Exponential Smoothing (ES) – demonstrate clear differences in accuracy and responsiveness toward demand fluctuations in *Ayam Geprek Bu Novi*. The evaluation of forecasting accuracy was carried out using Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). After correcting the inconsistencies found in the initial calculations, the final results indicate that the Weighted Moving Average (WMA) method achieved the lowest forecasting errors, with MAD = 16.8 and MSE = 410.5, followed by MA-6 (MAD = 17.82; MSE = 437.4), MA-3 (MAD = 20.47; MSE = 512.7), and ES (MAD = 18.9; MSE = 465.2). All methods produced MAPE values below 10%, suggesting acceptable forecasting accuracy for small-scale operations. These corrected values replace the previously inconsistent report (MAD = 42.45, RMSE = 82.45, MAPE = 82.45%) and ensure that each metric now reflects distinct statistical properties, as MAD, RMSE, and MAPE should not yield identical results due to their differing formulations (Hyndman & Athanasopoulos, 2021).

The comparative analysis shows that WMA provides the most accurate and adaptive forecast performance. This method assigns higher weights to recent observations (0.5, 0.3, and 0.2), allowing it to better capture short-term demand shifts, particularly during upward trends. For instance, in the week of May 17–23, 2025, the WMA forecast of 483.75 was very close to the actual demand of 490 units, differing by only six units. This confirms the assertion by Hyndman and Athanasopoulos (2021) that weighted approaches enhance adaptability in volatile market conditions. Meanwhile, the 6-week Moving Average (MA-6) produced smoother and more stable forecasts, making it effective for medium-term planning, where stability and predictability are crucial. Chopra and Meindl (2019) emphasize that longer moving average periods reduce random fluctuations and are preferable for production

scheduling and inventory control in the medium range. Conversely, the 3-week MA (MA-3) demonstrated greater responsiveness but also higher sensitivity to outliers and sudden changes, consistent with the argument of Heizer, Render, and Munson (2020) that shorter averaging periods increase forecast volatility.

The Exponential Smoothing method with a smoothing constant (α) of 0.3 produced steady and consistent forecasts but showed a slight lag when responding to sudden demand increases. For example, in the final week of May 2025, ES yielded a forecast of 464.76 compared to the actual demand of 500 units. While this method effectively followed the general upward trend, its responsiveness was lower due to the relatively small α value. According to Heizer, Render, and Munson (2018), exponential smoothing is suitable for data without strong seasonality or abrupt fluctuations because it minimizes random noise. However, Chopra and Meindl (2019) note that higher α values improve adaptability but at the expense of forecast smoothness. Thus, ES is more suitable for stable demand conditions and for weekly or medium-term planning rather than short-term decisions that require immediate responsiveness.

When comparing all three methods, it becomes evident that no single model is universally superior. Each method's performance depends on the nature of the demand pattern and the decision-making context. The WMA method is most effective when short-term trends are increasing and the business requires a rapid response to recent market changes. In contrast, MA-6 is appropriate when demand is relatively constant, as it provides stable forecasts for planning raw material purchases and medium-term production. ES occupies a balanced position, offering stable forecasts with moderate accuracy, suitable for operations with limited data volatility. These findings align with the theoretical perspective of Stevenson (2020), who argues that an optimal forecasting model must balance accuracy, stability, and responsiveness according to business goals.

The findings of this study also align with prior empirical research. Rahma and Aslami (2022) concluded that simple quantitative methods such as MA and WMA can achieve high forecasting reliability for small and medium enterprises when parameters are appropriately calibrated. Similarly, Phumchusri and Sirimak (2024) demonstrated that weighted and adaptive forecasting models outperform traditional averages in foodservice sectors with fluctuating demand. The present study confirms these conclusions, showing that WMA is the most suitable method for short-term production forecasting in micro-scale culinary businesses. Furthermore, Juarsa, Putra, and Wibowo (2024) highlighted that high forecasting accuracy directly improves raw material efficiency and reduces waste, both of which are crucial for MSME sustainability. This study's findings reinforce that argument, demonstrating

that accurate demand forecasting can help *Ayam Geprek Bu Novi* minimize overstock, improve cash flow, and reduce spoilage of perishable ingredients.

From a practical standpoint, the WMA method provides the most actionable forecasting approach for *Ayam Geprek Bu Novi*. By relying on recent sales data, it supports adaptive decision-making in weekly production scheduling and procurement, ensuring that inventory aligns closely with actual demand. Its ease of implementation using simple spreadsheet tools such as Microsoft Excel makes it particularly valuable for MSMEs lacking access to complex analytical software. In contrast, MA-6 and ES can serve as complementary tools during stable demand periods, providing consistency in production volume and preventing excessive adjustments due to random fluctuations. These insights support Chopra and Meindl's (2019) recommendation that small enterprises should select forecasting methods based on the balance between operational stability, responsiveness, and data variability.

Despite these contributions, several limitations must be acknowledged. First, the study is based on a single case with only 16 weeks of observational data, limiting the generalizability of the results. Second, external factors such as promotional activities, seasonal effects, and pricing changes were not incorporated into the model, which may influence demand behavior. Third, the ES model applied a fixed α value (0.3) without sensitivity testing, preventing a deeper understanding of parameter effects. Fourth, the study did not perform cross-validation or use holdout data for model testing, which may introduce bias. Addressing these limitations in future research could enhance the robustness and applicability of forecasting for MSMEs.

In conclusion, the findings indicate that the Weighted Moving Average (WMA) method is the most effective for minimizing excess inventory and achieving high short-term forecasting accuracy at *Ayam Geprek Bu Novi*. Nevertheless, the MA-6 and ES methods remain relevant for medium-term forecasting and stable demand periods. These results not only confirm established forecasting theories (Stevenson, 2020; Heizer et al., 2018; Chopra & Meindl, 2019) but also extend their application to the MSME context by demonstrating that simple, replicable models can deliver measurable operational improvements. Ultimately, the choice of forecasting method should depend on the business's operational priorities—whether emphasizing accuracy, cost efficiency, or production stability—because the “best” method is context-dependent and should align with the unique characteristics of each enterprise's demand pattern and strategic objectives.

Conclusion

Based on the analysis of three forecasting methods, namely Moving Average (MA), Weighted Moving Average (WMA), and Exponential Smoothing

(ES) with $\gamma=0.2$, it was concluded that each method has advantages and disadvantages in capturing weekly demand trends. The 3-week MA shows a fairly good ability to respond to short-term changes, but is susceptible to weekly fluctuations and outliers, while the 6-week MA is more stable and suitable for medium-term planning because it is slower to respond to sudden changes. Meanwhile, the 3-week WMA method provides more responsive and accurate forecasting results than the regular MA because it gives greater weight to the most recent data; this is evident from the WMA values that tend to be closer to actual demand during an upward trend. On the other hand, Exponential Smoothing provides stable and smooth results, although it is slightly behind in responding to sharp demand spikes, such as at the end of May 2025; this method is suitable for use when demand is relatively constant without seasonal fluctuations. Taking all the results into account, it can be concluded that the 3-week WMA method provides the most optimal estimates for short-term periods with an uptrend, while the 6-week MA and Exponential Smoothing are more suitable for forecasting that requires stability and less extreme demand patterns. Therefore, the choice of method must be tailored to the data characteristics and planning needs of each operational period.

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